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Introduction

Background and Purpose

As part of the Clean Air Act Amendments of 1990, Congress established a requirement under section 812 that EPA develop periodic Reports to Congress estimating the benefits and costs of the Clean Air Act itself. The first such report was to be a retrospective analysis, with a series of prospective analyses to follow every two years thereafter. This report represents the retrospective study, covering the period beginning with passage of the Clean Air Act Amendments of 1970, until 1990 when Congress enacted the most recent comprehensive amendments to the Act.

Since the legislative history associated with section 812 is sparse, there is considerable uncertainty regarding Congressional intent behind the requirement for periodic cost-benefit evaluations of the Clean Air Act (CAA). However, EPA believes the principal goal of these amendments was that EPA should develop, and periodically exercise, the ability to provide Congress and the public with up-to-date, comprehensive information about the economic costs, economic benefits, and health, welfare, and ecological effects of CAA programs. The results of such analyses might then provide useful information for refinement of CAA programs during future reauthorizations of the Act.

The retrospective analysis presented in this Report to Congress has been designed to provide an unprecedented examination of the overall costs and benefits of the historical Clean Air Act. Many other analyses have attempted to identify the isolated effects of individual standards or programs, but no analysis with the present degree of validity, breadth and integration has ever been successfully developed. Despite data limitations, considerable scientific uncertainties, and severe resource constraints; the EPA Project Team was able to develop a broad assessment of the costs and benefits associated with the major CAA programs of the 1970 to 1990 period. Beyond the statutory goals of section 812, EPA intends to use the results of this study to help support decisions on future investments in air pollution research. Finally, many of the methodologies and modeling systems developed for the retrospective study may be applied in the future to the ongoing series of section 812 prospective studies.

Clean Air Act Requirements, 1970 to 1990

The Clean Air Act establishes a framework for the attainment and maintenance of clean and healthful air quality levels. The Clean Air Act was enacted in 1970 and amended twice — in 1977 and most recently in 1990. The 1970 Clean Air Act contained a number of key provisions. First, EPA was directed to establish national ambient air quality standards for the major criteria air pollutants. The states were required to develop implementation plans describing how they would control emission limits from individual sources to meet and maintain the national standards. Second, the 1970 CAA contained deadlines and strengthened enforcement of emission limitations and state plans with measures involving both the states and the federal government. Third, the 1970 Act forced new sources to meet standards based on the best available technology. Finally, the Clean Air Act of 1970 addressed hazardous pollutants and automobile exhausts.

The 1977 Clean Air Act Amendments also set new requirements on clean areas already in attainment with the national ambient air quality standards. In addition, the 1977 Amendments set out provisions to help areas that failed to comply with deadlines for achievement of the national ambient air quality standards. For example, permits for new major sources and modifications were required.

The 1990 Clean Air Act Amendments considerably strengthened the earlier versions of the Act. With respect to nonattainment, the Act set forth a detailed and graduated program, reflecting the fact that problems in some areas are more difficult and complex than others. The 1990 Act also established a list of 189 regulated hazardous air pollutants and a multi-step program for controlling emissions of these toxic air pollutants. Significant control programs were also established for emissions of acid rain precursors and stratospheric ozone-depleting chemicals. The biggest regulatory procedural change in the Act is the new permit program where all major sources are now required to obtain an operating permit. Finally, the amendments considerably expanded the enforcement provisions of the Clean Air Act, adding administrative penalties and increasing potential civil penalties.

Section 812 of the Clean Air Act Amendments of 1990

Section 812 of the Clean Air Act Amendments of 1990 requires the EPA to perform a "retrospective" analysis which assesses the costs and benefits to the public health, economy and the environment of clean air legislation enacted prior to the 1990 amendments. Section 812 directs that EPA shall measure the effects on "employment, productivity, cost of living, economic growth, and the overall economy of the United States" of the Clean Air Act. Section 812 also requires that EPA consider all of the economic, public health, and environmental benefits of efforts to comply with air pollution standards. Finally, section 812 requires EPA to evaluate the prospective costs and benefits of the Clean Air Act every two years.

Analytical Design and Review

Target Variable

The retrospective analysis was designed to answer the following question:

"How do the overall health, welfare, ecological, and economic benefits of Clean Air Act programs compare to the costs of these programs?"

By examining the overall effects of the Clean Air Act, this analysis complements the Regulatory Impact Analyses (RIAs) developed by EPA over the years to evaluate individual regulations. Resources were used more efficiently by recognizing that these RIAs, and other EPA analyses, provide complete information about the costs and benefits of specific rules. Furthermore, in addition to the fact that the RIAs already provide rule-specific benefit and cost estimates, the broad-scale approach adopted in the present study precludes reliable re-estimation of the benefits and costs of individual standards or programs. On the cost side, this study relies on aggregated compliance expenditure data from existing surveys. Unfortunately, these data do not support reliable allocation of total costs incurred to specific emissions reductions for the various pollutants emitted from individual facilities. Therefore, it is infeasible in the context of this study to assign costs to specific changes in emissions. Further complications emerge on the benefit side. To estimate benefits, this study calculates the change in incidences of adverse effects implied by changes in ambient concentrations of air pollutants. However, reductions achieved in emitted pollutants contribute to changes in ambient concentrations of those, or secondarily formed, pollutants in ways which are highly complex, interactive, and often nonlinear. Therefore, even if costs could be reliably matched to changes in emissions, benefits cannot be reliably matched to changes in emissions because of the complex, nonlinear relationships between emissions and the changes in ambient concentrations which are used to estimate benefits.

Focusing on the broader target variables of "overall costs" and "overall benefits" of the Clean Air Act, the EPA Project Team adopted an approach based on construction and comparison of two distinct scenarios: a "no-control scenario" and a "control scenario." The no-control scenario essentially freezes federal, state, and local air pollution controls at the levels of stringency and effectiveness which prevailed in 1970. The control scenario assumes that all federal, state, and local rules promulgated pursuant to, or in support of, the CAA during 1970 to 1990 were implemented. This analysis then estimates the differences between the economic and environmental outcomes associated with these two scenarios. For more information on the scenarios and their relationship to historical trends, see Appendix B.

Key Assumptions

Two key assumptions were made during the scenario design process to avoid miring the analytical process in endless speculation. First, the "no-control" scenario was defined to reflect the assumption that no additional air pollution controls were imposed by any level of government or voluntarily initiated by private entities after 1970. Second, it is assumed that the geographic distribution of population and economic activity remains the same between the two scenarios.

The first assumption is an obvious oversimplification. In the absence of the CAA, one would expect to see some air pollution abatement activity, either voluntary or due to state or local regulations. It is conceivable that state and local regulation would have required air pollution abatement equal to—or even greater than—that required by the CAA; particularly since some states, most notably California, have done so. If one were to assume that state and local regulations would have been equivalent to CAA standards, then a cost-benefit analysis of the CAA would be a meaningless exercise since both costs and benefits would equal zero. Any attempt to predict how state and local regulations would have differed from the CAA would be too speculative to support the credibility of the ensuing analysis. Instead, the no-control scenario has been structured to reflect the assumption that states and localities would not have invested further in air pollution control programs after 1970 in the absence of the federal CAA. That is, this analysis accounts for the costs and benefits of all air pollution control from 1970 to 1990. Speculation about the precise fraction of costs and benefits attributable exclusively to the federal CAA is left to others. Nevertheless, it is important to note that state and local governments and private initiatives are responsible for a significant portion of these total costs and total benefits. At the same time, it must also be acknowledged that the federal CAA played an essential role in achieving these results by helping minimize the advent of pollution havens[1], establishing greater incentives for pollution control research and development than individual state or local rules could provide; organizing and promoting health and environmental research, technology transfer and other information management and dissemination services; addressing critical interstate air pollution problems, including the regional fine particle pollution which is responsible for much of the estimated monetary benefit of historical air pollution control; providing financial resources to state and local government programs; and many other services. In the end, however, the benefits of historical air pollution controls were achieved through partnerships among all levels of government and with the active participation and cooperation of private entities and individuals.

The second assumption concerns changing demographic patterns in response to air pollution. In the hypothetical no-control world, air quality is worse than that in the historical "control" world particularly in urban industrial areas. It is possible that in the no-control case more people, relative to the control case, would move away from the most heavily polluted areas. Rather than speculate on the scale of population movement, the analysis assumes no differences in demographic patterns between the two scenarios. Similarly, the analysis assumes no changes in the spatial pattern of economic activity. For example: if, in the no-control case, an industry is expected to produce greater output than it did in the control case, that increased output is produced by actual historical plants, avoiding the need to speculate about the location or other characteristics of new plants providing additional productive capacity.

Analytic Sequence

The analysis was designed and implemented in a sequential manner following seven basic steps which are summarized below and described in detail later in this report. The seven major steps were:

- direct cost estimation
- macroeconomic modeling
- emissions modeling
- air quality modeling
- health and environmental effects estimation
- economic valuation
- results aggregation and uncertainty characterization

By necessity, these components had to be completed sequentially. The emissions modeling effort had to be completed entirely before the air quality models could be configured and run; the air quality modeling results had to be completed before the health and environmental consequences of air quality changes could be derived; and so on. The analytical sequence, and the modeled versus actual data basis for each analytical component, are summarized in Figure 1 and described in the remainder of this section.

The first step of the analysis was to estimate the total direct costs incurred by public and private entities to comply with post-1970 CAA requirements. These data were obtained directly from Census Bureau and Bureau of Economic Analysis (BEA) data on compliance expenditures reported by sources, and from EPA analyses. These direct cost data were then adopted as inputs to the macroeconomic model used to project economic conditions–such as production levels, prices, employment patterns, and other economic indicators–under the two scenarios. To ensure a consistent basis for scenario comparison, the analysis applied the same macroeconomic modeling system to estimate control and no-control scenario economic conditions.[2] First, a control scenario was constructed by running the macroeconomic model using actual historical data for input factors such as economic growth rates during the 1970 to 1990 period. The model was then re-run for the no-control scenario by, in essence, returning all post-1970 CAA compliance expenditures to the economy. With these additional resources available for capital formation, personal consumption, and other purposes, overall economic conditions under the no-control scenario differed from those of the control scenario. In addition to providing estimates of the difference in overall economic growth and other outcomes under the two scenarios, these first two analytical steps were used to define specific economic conditions used as inputs to the emissions modeling effort, the first step in the estimation of CAA benefits.[3]

[1] "Pollution havens" is a term used to identify individual states or localities which permit comparatively high levels of pollution in order to attract and hold polluting industries and other activities.

[2] Using modeled economic conditions for both scenarios has both advantages and disadvantages. The principal disadvantage is that historical economic conditions "predicted" by a macroeconomic model will not precisely duplicate actual historical events and conditions. However, this disadvantage is outweighed by the avoidance of distortions and biases which would result from comparing a modeled no-control scenario with actual historical conditions. By using the same macroeconomic model for both scenarios, model errors and biases essentially cancel out, yielding more robust estimates of scenario differences, which are what this analysis seeks to evaluate.

[3] For example, the macroeconomic model projected different electricity sales levels under the two scenarios, and these sales levels were used as key input assumptions by the utility sector emissions model.

Figure 1. Summary of Analytical Sequence and Modeled versus Historical Data Basis.

Control Scenario		**No-Control Scenario**
	Compile historical compliance expenditure data	
Develop modeled macroeconomic scenario based on actual historical economic data		Develop modeled macroeconomic scenario by rerunning control scenario with compliance expenditures added back to the economy
Project emissions by year, pollutant, and sector using control scenario macroeconomic projection as input to sector-specific emissions models		Re-run sector-specific emissions models using no-control scenario macroeconomic projection
Develop statistical profiles of historical air quality for each pollutant based on historical monitoring data (plus extrapolations to cover unmonitored areas)		Derive no-control air quality profiles by adjusting control scenario profiles based on differences in air quality modeling of control scenario and no-control scenario emissions inventories
Estimate physical effects based on application of concentration-response functions to historical air quality profiles		Estimate physical effects based on application of concentration-response functions to no-control scenario air quality profiles
	Calculate differences in physical outcomes between control and no-control scenario	
	Estimate economic value of differences in physical outcomes between the two scenarios*	
	Compare historical, direct compliance costs with estimated economic value of monetized benefits, considering additional benefits which could not be quantified and/or monetized	

* In some cases, economic value is derived directly from physical effects modeling (e.g., agricultural yield loss).

Using appropriate economic indicators from the macroeconomic model results as inputs, a variety of emissions models were run to estimate emissions levels under the two scenarios. These emissions models provided estimates of emissions of six major pollutants[4] from each of six key emitting sectors: utilities, industrial processes, industrial combustion, on-highway vehicles, off-highway vehicles, and commercial/residential sources. The resulting emissions profiles reflect state-wide total emissions from each pollutant-sector combination for the years 1975, 1980, 1985, and 1990.[5]

The next step toward estimation of benefits involved translating these emissions inventories into estimates of air quality conditions under each scenario. Given the complexity, data requirements, and operating costs of state-of-the-art air quality models–and the afore-mentioned resource constraints–the EPA Project Team adopted simplified, linear scaling approaches for a number of pollutants. However, for ozone and other pollutants or air quality conditions which involve substantial non-linear formation effects and/or long-range atmospheric transport and transformation, the EPA Project Team invested the time and resources needed to use more sophisticated modeling systems. For example, urban area-specific ozone modeling was conducted for 147 urban areas throughout the 48 contiguous states.

Up to this point of the analysis, both the control and no-control scenario were based on modeled conditions and outcomes. However, at the air quality modeling step, the analysis returned to a foundation based on actual historical conditions and data. Specifically, actual historical air quality monitoring data from 1970 to 1990 were used to define the control scenario. Air quality conditions under the no-control scenario were then derived by scaling the historical data adopted for the control scenario by the ratio of the modeled control and no-control scenario air quality. This approach took advantage of the richness of the historical data on air quality, provided a realistic grounding for the benefit measures, and yet retained the analytical consistency conferred by using the same modeling approach for both scenarios. The outputs of this step of the analysis were statistical profiles for each pollutant characterizing air quality conditions at each monitoring site in the lower 48 states.[6]

The control and no-control scenario air quality profiles were then used as inputs to a modeling system which translates air quality to physical outcomes –such as mortality, emergency room visits, or crop yield losses– through the use of concentration-response functions. These concentration-response functions were in turn derived from studies found in the scientific literature on the health and ecological effects of air pollutants. At this point, estimates were derived of the differences between the two scenarios in terms of incidence rates for a broad range of human health and other effects of air pollution by year, by pollutant, and by monitor.[7]

In the next step, economic valuation models or coefficients were used to estimate the economic value of the reduction in incidence of those adverse effects which were amenable to such monetization. For example, a distribution of unit values derived from the economic literature was used to estimate the value of reductions in mortality risk associated with exposure to particulate matter. In addition, benefits which could not be expressed in economic terms were compiled and are presented herein. In some cases, quantitative estimates of scenario differences in the incidence of a nonmonetized effect were calculated.[8] In many other cases, available data and techniques were insufficient to support anything more than a qualitative characterization of the change in effects.

Finally, the costs and monetized benefits were combined to provide a range of estimates for the partial, net economic benefit of the CAA with the range reflecting quantified uncertainties associated with the physical effects and economic valuation steps.[9] The term "partial" is emphasized because only a subset of the total potential benefits of the CAA could be represented in economic terms due to limitations in ancal

[4] These six pollutants are total suspended particulates (TSP), sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO), volatile organic compounds (VOCs), and lead (Pb). The other CAA criteria pollutant, ozone (O_3), is formed in the atmosphere through the interaction of sunlight and ozone precursor pollutants such as NO_x and VOCs.

[5] By definition, 1970 emissions under the two scenarios are identical.

[6] The one exception is particulate matter (PM). For PM, air quality profiles for both Total Suspended Particulates (TSP) and particulates less than or equal to 10 microns in diameter (PM_{10}) were constructed at the county level rather than the individual monitor level.

[7] Or, for PM, by county.

[8] For example, changes in forced expiratory volume in one second (FEV_1) as a result of exposure to ozone were quantified but could not be expressed in terms of economic value.

[9] Although considerable uncertainties surround the direct cost, macroeconomic modeling, emissions modeling,, and air quality modeling steps, the ranges of aggregate costs and benefits presented in this analysis do not reflect these uncertainties. While the uncertainties in these components were assessed qualitatively, and in some cases quantitatively, resource limitations precluded the multiple macroeconomic model, emissions model, and air quality model runs which would have been required to propagate these uncertainties through the entire analytical sequence. As a result, complete quantitative measures of the aggregate uncertainty in the cost and benefit estimates could not be derived. However, the ranges presented do reflect quantitative measures of the uncertainties in the two most uncertain analytical steps: physical effects estimation and economic valuation.

cal resources, available data and models, and the state of the science.[10] Of paramount concern to the EPA Project Team was the paucity of concentration-response functions needed to translate air quality changes into measures of ecological effect. In addition, significant scientific evidence exists linking air pollution to a number of adverse human health effects which could not be effectively quantified and/or monetized.[11]

Review Process

The CAA requires EPA to consult with an outside panel of experts–referred to statutorily as the Advisory Council on Clean Air Act Compliance Analysis (the Council)–in developing the section 812 analyses. In addition, EPA is required to consult with the Department of Labor and the Department of Commerce.

The Council was organized in 1991 under the auspices and procedures of EPA's Science Advisory Board (SAB). Organizing the review committee under the SAB ensured that review of the section 812 studies would be conducted by highly qualified experts in an objective, rigorous, and publicly open manner. The Council has met many times during the development of the retrospective study to review methodologies and interim results. While the full Council retains overall review responsibility for the section 812 studies, some specific issues concerning physical effects and air quality modeling have been referred to subcommittees comprised of both Council members and members of other SAB committees. The Council's Physical Effects Review Subcommittee met several times and provided its own review findings to the full Council. Similarly, the Council's Air Quality Subcommittee, comprised of members and consultants of the SAB Clean Air Scientific Advisory Committee (CASAC), held several teleconference meetings to review methodology proposals and modeling results.

With respect to the interagency review process, EPA expanded the list of consulted agencies and convened a series of meetings during the design and early implementation phases from 1991 through late 1994. In late 1994, to ensure that all interested parties and the public received consistent information about remaining analytical issues and emerging results, EPA decided to use the public SAB review process as the primary forum for presenting and discussing issues and results. The Interagency Review Group was therefore discontinued as a separate process in late 1994.

A final, brief interagency review, pursuant to Circular A-19, was organized in August 1997 by the Office of Management and Budget and conducted following the completion of the extensive expert panel peer review by the SAB Council. During the course of the final interagency discussions, it became clear that several agencies held different views pertaining to several key assumptions in this study as well as to the best techniques to apply in the context of environmental program benefit-cost analyses, including the present study. The concerns include: (1) the extent to which air quality would have deteriorated from 1970 to 1990 in the absence of the Clean Air Act, (2) the methods used to estimate the number of premature deaths and illnesses avoided due to the CAA, (3) the methods used to estimate the value that individuals place on avoiding those risks, and (4) the methods used to value non-health related benefits. However, due to the court deadline the resulting concerns were not resolved during this final, brief interagency review. Therefore, this report reflects the findings of EPA and not necessarily other agencies in the Administration. Interagency discussion of some of these issues will continue in the context of the future prospective section 812 studies and potential regulatory actions.

Report Organization

The remainder of the main text of this report summarizes the key methodologies and findings of retrospective study. The direct cost estimation and macroeconomic modeling steps are presented in Chapter 2. The emissions modeling is summarized in Chapter 3. Chapter 4 presents the air quality modeling methodology and sample results. Chapter 5 describes the approaches used and principal results obtained through the physical effects estimation process. Economic valuation methodologies are described in Chapter 6. Chapter 7 presents the aggregated results of the cost and benefit estimates and describes and evaluates important uncertainties in the results.

Additional details regarding the methodologies and results are presented in the appendices and in the referenced supporting documents. Appendix A covers the direct cost and macroeconomic modeling. Appendix B provides additional detail on the sector-specific emissions modeling effort. Details of the air quality models used and results obtained are presented or referenced in Appendix C. The effects of the CAA on human health and visibility; aquatic, wetland, and forest ecosystems; and agriculture are presented in Appendices D, E, and F, respectively. Appendix G presents details of the lead (Pb) benefits analysis. Air toxics reduction benefits are discussed in Appendix H. The methods and assumptions used to value quantified effects of the CAA in economic terms are described in Appendix I. Appendix J describes some areas of research which may increase comprehensiveness and reduce uncertainties in effect estimates for future assessments, and describes plans for future section 812 analyses.

[10] It should be noted that there is some uncertainty associated with the estimates of economic costs as well and that some omitted components of adverse economic consequences of pollution control programs may be significant. For example, some economists argue that the economic costs of the CAA reported herein may be significantly underestimated to the extent potential adverse effects of regulation on technological innovation are not captured. Nevertheless, it is clear that the geographic, population, and categorical coverage of monetary cost effects is significantly greater than coverage of monetized benefits in this analysis.

[11] For example, while there is strong evidence of a link between exposure to carbon monoxide and reduced time of onset of angina attack, there are no valuation functions available to estimate the economic loss associated with this effect.

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Cost and Macroeconomic Effects

The costs of complying with Clean Air Act (CAA) requirements through the 1970 to 1990 period affected patterns of industrial production, capital investment, productivity, consumption, employment, and overall economic growth. The purpose of the analyses summarized in this chapter was to estimate those direct costs and the magnitude and significance of resulting changes to the overall economy. This was accomplished by comparing economic indicators under two alternative scenarios: a control scenario serving as the historical benchmark, including the historical CAA as implemented; and a no-control scenario which assumes historical CAA programs did not exist. The estimated economic consequences of the historical CAA were taken as the difference between these two scenarios.

Data used as inputs to the cost analysis can be classified into two somewhat overlapping categories based on the information source: survey-based information (generally gathered by the Census Bureau) and information derived from various EPA analyses. For the most part, cost estimates for stationary air pollution sources (e.g., factory smokestacks) are based on surveys of private businesses that attempt to elicit information on annual pollution control outlays by those businesses. Estimates of pollution control costs for mobile sources (e.g., automobiles) are largely based on EPA analyses, rather than on direct observation and measurement of compliance expenditures. For example, to determine one component of the cost of reducing lead emissions from mobile sources, the Project Team used an oil refinery production cost model to calculate the incremental cost required to produce unleaded (or less-leaded, as appropriate) rather than leaded gasoline, while maintaining the octane level produced by leaded gasoline.

As is the case with many policy analyses, a significant uncertainty arises in the cost analysis as a consequence of constructing a hypothetical scenario. With this retrospective analysis covering almost twenty years, difficulties arise in projecting alternative technological development paths. In some cases, the analytical assumptions used to project the alternative scenario are not immediately apparent. For example, the surveys covering stationary source compliance expenditures require respondents to report pollution abatement expenditures—implicitly asking them to determine by how much the company's costs would decline if there were no CAA compliance requirements. While a response might be relatively straightforward in the few years following passage of the CAA, a meaningful response becomes more difficult after many years of technical change and investment in less-polluting plant and equipment make it difficult to determine the degree to which total costs would differ under a "no CAA" scenario. In cases such as this, assumptions concerning the alternative hypothetical scenario are made by thousands of individual survey respondents. Where cost data are derived from EPA analyses, the hypothetical scenario assumptions are, at least in theory, more apparent. For example, when determining the incremental cost caused by pollution-control requirements, one needs to make assumptions (at least implicitly) about what an auto would look like absent pollution control requirements. In either case, the need to project hypothetical technology change for two decades introduces uncertainty into the assessment results, and this uncertainty may be difficult to quantify.

The remainder of this chapter summarizes the basic methods and results of the direct compliance cost and macroeconomic analyses. Further details regarding the modeling methods and assumptions employed, as well as additional analytical results, are presented in Appendix A.

Direct Compliance Costs

Compliance with the CAA imposed direct costs on businesses, consumers, and governmental units; and triggered other expenditures such as governmental regulation and monitoring costs and expenditures for

Table 1. Estimated Annual CAA Compliance Costs ($billions).

	Expenditures		Annualized Costs $1990 at:		
Year	$current	$1990	3%	5%	7%
1973	7.2	19.6	11.0	11.0	11.1
1974	8.5	21.4	13.2	13.4	13.7
1975	10.6	24.4	13.3	13.6	14.0
1976	11.2	24.1	14.1	14.6	15.1
1977	11.9	24.1	15.3	15.9	16.6
1978	12.0	22.6	15.0	15.8	16.7
1979	14.4	24.8	17.3	18.3	19.3
1980	16.3	25.7	19.7	20.8	22.0
1981	17.0	24.4	19.6	20.9	22.3
1982	16.0	21.6	18.6	20.1	21.7
1983	15.5	20.1	19.1	20.7	22.5
1984	17.3	21.6	20.1	21.9	23.8
1985	19.1	22.9	22.5	24.4	26.5
1986	17.8	20.8	21.1	23.2	25.4
1987	18.2	20.6	22.1	24.2	26.6
1988	18.2	19.8	22.0	24.3	26.7
1989	19.0	19.8	22.9	25.3	27.8
1990	19.0	19.0	23.6	26.1	28.7

research and development by both government and industry. Although expenditures unadjusted for inflation — that is, expenditures denominated in "current dollars"— increased steadily from $7 billion to $19 billion per year over the 1973 to 1990 period,[12] annual CAA compliance expenditures adjusted for inflation were relatively stable, averaging near $25 billion (in 1990 dollars) during the 1970s and close to $20 billion during most of the 1980s (see Table 1). Aggregate compliance expenditures were somewhat less than one half of one percent of total domestic output during that period, with the percentage falling from two thirds of one percent of total output in 1975 to one third of one percent in 1990.

Although useful for many purposes, a summary of direct annual expenditures may not the best cost measure to use when comparing costs to benefits. Capital expenditures are investments, generating a stream of benefits and opportunity cost[13] over the life of the investment. The appropriate accounting technique to use for capital expenditures in a cost/benefit analysis is to annualize the expenditure. This technique, analogous to calculating the monthly payment associated with a home mortgage, involves spreading the cost of the capital equipment over the useful life of the equipment using a discount rate to account for the time value of money.

For this cost/benefit analysis, "annualized" costs reported for any given year are equal to O&M expenditures — including R&D and other similarly recurring expenditures — plus amortized capital costs (i.e., depreciation plus interest costs associated with the existing capital stock) for that year. Stationary source air pollution control capital costs were amortized over 20 years; mobile source air pollution control costs were amortized over 10 years.[14] All capital expenditures were annualized using a five percent, inflation-adjusted rate of interest. Additionally, annualized costs were calculated using discount rates of three and seven percent to determine the sensitivity of the cost results to changes in the discount rate. Table 1 summarizes costs annualized at three, five, and seven percent, as well as annual expenditures.

Total expenditures over the 1973-1990 period, discounted to 1990 using a five percent (net of inflation) discount rate, amount to 628 billion dollars (in 1990 dollars). Discounting the annualized cost stream to 1990 (with both annualization and discounting procedures using a five percent rate) gives total costs of 523 billion dollars (in 1990 dollars). Aggregate annualized costs are less than expenditures because the annualization procedure spreads some of the capital cost beyond 1990.[15]

[12] Due to data limitations, the cost analysis for this CAA retrospective starts in 1973, missing costs incurred in 1970-72. This limitation is not likely to be significant, however, because relatively little in the way of compliance with the "new" provisions of the 1970 CAA was required in the first two years following passage.

[13] In this context, "opportunity cost" is defined as the value of alternative investments or other uses of funds foregone as a result of the investment.

[14] Although complete data are available only for the period 1973-1990, EPA's Cost of Clean report includes capital expenditures for 1972 (see Appendix A for more details and complete citation). Those capital expenditure data have been used here. Therefore, amortized costs arising from 1972 capital investments are included in the 1973-1990 annualized costs, even though 1972 costs are not otherwise included in the analysis. Conversely, some capital expenditures incurred in the 1973-1990 period are not reflected in the 1973-1990 annualized costs — those costs are spread through the following two decades, thus falling outside of the scope of this study (e.g., only one year of depreciation and interest expense is included for 1989 capital expenditures). Similarly, benefits arising from emission reductions realized after 1990 as a result of capital investments made during the 1970 to 1990 period of this analysis are not included in the estimates of benefits included in this report.

[15] This adjustment is required because many 1970 to 1990 investments in control equipment continue to yield benefits beyond 1990. Annualization of costs beyond 1990 ensures that the costs and benefits of any particular investment are properly scaled and matched over the lifetime of the investment.

Indirect Effects of the CAA

Through changing production costs, CAA implementation induced changes in consumer good prices, and thus in the size and composition of economic output. The Project Team used a general equilibrium macroeconomic model to assess the extent of such second-order effects. This type of model is useful because it can capture the feedback effects of an action. In the section 812 macroeconomic modeling exercise, the feedback effects arising from expenditure changes were captured, but the analogous effects arising from improvements in human health were not captured by the model. For example, the macroeconomic model results do not reflect the indirect economic effects of worker productivity improvements and medical expenditure savings caused by the CAA. Consequently, the macroeconomic modeling exercise provides limited and incomplete information on the type and potential scale of indirect economic effects.

The effects estimated by the macroeconomic model can be grouped into two broad classes: sectoral impacts (i.e., changes in the composition of economic output), and aggregate effects (i.e., changes in the degree of output or of some measure of human welfare). The predicted sectoral effects were used as inputs to the emissions models as discussed in Chapter 3. In general, the estimated second-order macroeconomic effects were small relative to the size of the U.S. economy. See Appendix A for more detail on data sources, analytical methods, and results for the macroeconomic modeling performed for this assessment.

Sectoral Impacts

The CAA had variable compliance impacts across economic sectors. The greatest effects were on the largest energy producers and consumers, particularly those sectors which relied most heavily on consumption of fossil fuels (or energy generated from fossil fuels). In addition, production costs increased more for capital-intensive industries than for less capital-intensive industries under the control scenario due to a projected increase in interest rates. The interest rate increase, which resulted in an increase in the cost of capital, occurred under the control scenario because CAA-mandated investment in pollution abatement reduced the level of resources available for other uses, including capital formation.

Generally, the estimated difference in cost impacts under the control and no-control scenarios for a particular economic sector was a function of the relative energy-intensity and capital-intensity of that sector. Increased production costs in energy- and capital-intensive sectors under the control scenario were reflected in higher consumer prices, which resulted in reductions in the quantity of consumer purchases of goods and services produced by those sectors. This reduction in consumer demand under the control scenario led, ultimately, to reductions in output and employment in those sectors. The sectors most affected by the CAA were motor vehicles, petroleum refining, and electricity generation. The electricity generation sector, for example, incurred a two to four percent increase in consumer prices by 1990, resulting in a three to five and a half percent reduction in output. Many other manufacturing sectors saw an output effect in the one percent range.

Some other sectors, however, were projected to increase output under the control scenario. Apart from the pollution control equipment industry, which was not separately identified and captured in the macroeconomic modeling performed for this study, two example sectors for which output was higher and prices were lower under the control scenario are food and furniture. These two sectors showed production cost and consumer price reductions of one to two percent relative to other industries under the control scenario, resulting in output and employment increases of similar magnitudes.

Aggregate Effects

As noted above, the control and no-control scenarios yield different estimated mixes of investment. In particular, the control scenario was associated with more pollution control capital expenditure and less consumer commodity capital expenditure. As a result, the growth pattern of the economy under the control scenario differed from the no-control scenario. Under the control scenario, the macroeconomic model projected a rate of long-run GNP growth about one twentieth of one percent per year lower than under the no-control scenario. Aggregating these slower growth effects of the control scenario over the entire 1970 to 1990 period of this study results, by 1990, in a level of GNP one percent (or approximately $55 billion) lower than that projected under the no-control scenario.

Although small relative to the economy as a whole, the estimated changes in GNP imply that the potential impact of the CAA on the economy by 1990 was greater than that implied by expenditures ($19 billion in 1990) or annualized costs ($26 billion in 1990, annualized at five percent). Discounting the stream of 1973-1990 GNP effects to 1990 gives an aggregate impact on production of 1,005 billion dollars (in 1990 dollars discounted at five percent). Of that total, $569 billion represent reductions in household consumption, and another $200 billion represent government consumption, for an aggregate effect on U.S. consumption of goods and services equal to 769 billion dollars. Both the aggregate GNP effects and aggregate consumption effects exceed total 1973-1990 expenditures ($628 billion) and annualized costs ($523 billion, with all dollar quantities in $1990, discounted at five percent).

Changes in GNP (or, even, changes in the national product account category "consumption") do not necessarily provide a good indication of changes in social welfare. Social welfare is not improved, for example, by major oil tanker spills even though measured GNP is increased by the "production" associated with clean-up activities. Nevertheless, the effects of the CAA on long-term economic growth would be expected to have had some effect on economic welfare. One of the characteristics of the macroeconomic model used by the Project Team is its ability to estimate a measure of social welfare change which is superior to GNP changes. This social welfare measure estimates the monetary compensation which would be required to offset the losses in consumption (broadly defined) associated with a given policy change. The model reports a range of results, with the range sensitive to assumptions regarding how cost impacts are distributed through society. For the CAA, the model reports an aggregate welfare effect of 493 billion to 621 billion dollars (in 1990 dollars), depending on the distributional assumptions used. This range does not differ greatly from the range of results represented by 1973-1990 expenditures, compliance costs, and consumption changes.

Uncertainties and Sensitivities in the Cost and Macroeconomic Analysis

The cost and macroeconomic analyses for the present assessment relied upon survey responses, EPA analyses, and a macroeconomic simulation model. Although the Project Team believes that the results of the cost and macroeconomic analyses are reasonably reliable, it recognizes that every analytical step is subject to uncertainty. As noted at the beginning of this chapter, explicit and implicit assumptions regarding hypothetical technology development paths are crucial to framing the question of the cost impact of the CAA. In addition, there is no way to verify the accuracy of the survey results used;[16] alternative, plausible cost analyses exist that arrive at results that differ from some of the results derived from EPA analyses; and it is not clear how the use of a general equilibrium macroeconomic model affects the accuracy of macroeconomic projections in a macroeconomy characterized by disequilibrium. For many factors engendering uncertainty, the degree or even the direction of bias is unknown. In several areas, nevertheless, uncertainties and/or sensitivities can be identified that may bias the results of the analysis.

Productivity and Technical Change

An important component of the macroeconomic model used by the Project Team is its treatment of technical change and productivity growth. Three factors associated with productivity and technical change have been identified which may bias the results of the macroeconomic simulation: (1) the long-run effects of reducing the "stock" of technology, (2) the possible "chilling" effect of regulations on innovation and technical change, and (3) the role of endogenous productivity growth within the macroeconomic model.

The macroeconomic model projected a decrease in the growth of GNP as a result of CAA compliance. Decreased growth was due not only to decreased capital investment, but also to decreased factor productivity. The annual decrement in productivity can be thought of as a reduction of the stock of available technology. That reduction in stock could be expected to affect macroeconomic activity after 1990, as well as

[16] For an example of the difficulties one encounters in assessing the veracity of survey results, see the discussion in Appendix A on the apparently anomalous growth in stationary source O&M expenditures in relation to the size of the stationary source air pollution control capital stock.

during the 1973-1990 period studied by the Project Team. Thus, to the extent that this effect exists, the Project Team has underestimated the macroeconomic impact of the CAA by disregarding the effect of 1973-1990 productivity change decrements on post-1990 GNP.

Some economists contend that regulations have a "chilling" effect on technological innovation and, hence, on productivity growth. Two recent studies by Gray and Shadbegian,[17] which are sometimes cited in support of this contention, suggest that pollution abatement regulations may decrease productivity levels in some manufacturing industries. The macroeconomic model allowed policy-induced productivity change through the mechanism of price changes and resultant factor share changes. To the extent that additional policy-induced effects on productivity growth exist, the Project Team has underestimated the impact of the CAA on productivity growth during the 1973-1990 period, and, thus, has underestimated macroeconomic impacts during the 1973-1990 period and beyond.

The macroeconomic model allowed productivity growth to vary with changes in prices generated by the model. This use of "endogenous" productivity growth is not universal in the economic growth literature — that is, many similar macroeconomic models do not employ analogous forms of productivity growth. The Project Team tested the sensitivity of the model results to the use of endogenous productivity growth. If the model is run without endogenous productivity growth, then the predicted macroeconomic impacts (GNP, personal consumption, etc.) of the CAA are reduced by approximately 20 percent. That is, to the extent that use of endogenous productivity growth in the macroeconomic model is an inaccurate simulation technique, then the Project Team has overestimated the macroeconomic impact of the CAA.

Discount Rates

There is a broad range of opinion in the economics profession regarding the appropriate discount rate to use in analyses such as the current assessment. Some economists believe that the appropriate rate is one that approximates the social rate of time preference — that is, the rate of return at which individuals are willing to defer consumption to the future. A three percent rate would approximate the social rate of time preference (all rates used here are "real", i.e., net of price inflation impacts). Others believe that a rate that approximates the opportunity cost of capital (e.g., seven percent or greater) should be used.[18] A third school of thought holds that some combination of the social rate of time preference and the opportunity cost of capital is appropriate, with the combination effected either by use of an intermediate rate or by use of a multiple-step procedure employing the social rate of time preference as the "discount rate," but still accounting for the opportunity cost of capital.

The Project Team elected to use an intermediate rate (five percent), but recognizes that analytical results aggregated across the study period are sensitive to the discount rate used. Consequently, all cost measures are presented at three and seven percent, as well as the base case five percent. Table 2 summarizes major cost and macroeconomic impact measures expressed in constant 1990 dollars, and discounted to 1990 at rates of three, five, and seven percent.

Table 2. Compliance Cost, GNP, and Consumption Impacts Discounted to 1990 ($1990 billions)

	3%	5%	7%
Expenditures	$52	628	761
Annualized Costs	417	523	657
GNP	880	1005	1151
Household Consumption	500	569	653
HH and Gov't Consumption	676	769	881

[17] Gray, Wayne B., and Ronald J. Shadbegian, "Environmental Regulation and Manufacturing Productivity at the Plant Level," Center for Economic Studies Discussion Paper, CES 93-6, March 1993. Gray, Wayne B., and Ronald J. Shadbegian, "Pollution Abatement Costs, Regulation, and Plant-Level Productivity," National Bureau of Economic Research, Inc., Working Paper Series, Working Paper No. 4994, January 1995.

[18] Some would argue that use of the opportunity cost of capital approach would be inappropriate in the current assessment if the results of the macroeconomic modeling (such as GNP) were used as the definition of "cost," since the macro model already accounts for the opportunity cost of capital. The appropriate rate would then be the social rate of time preference.

Exclusion of Health Benefits from the Macroeconomic Model

The macroeconomic modeling exercise was designed to capture the second-order macroeconomic effects arising from CAA compliance expenditures. Those predicted second-order effects are among the factors used to drive the emissions estimates and, ultimately, the benefits modeled for this assessment. The benefits of the CAA, however, would also be expected to induce second-order macroeconomic effects. For example, increased longevity and decreased incidence of non-fatal heart attacks and strokes would be expected to improve macroeconomic performance measures. The structure of the overall analysis, however, necessitated that these impacts be excluded from the macroeconomic simulation.

The first-order CAA beneficial effects have been included in the benefits analysis for this study, including measures that approximate production changes (e.g., income loss due to illness, or lost or restricted work days; income loss due to impaired cognitive ability; and income loss due to reduced worker production in certain economic sectors). These measures are analogous to compliance expenditures in the cost analysis. The second-order benefits impacts, which would result from price changes induced by CAA-related benefits, have not been estimated. It is likely that the estimated adverse second-order macroeconomic impacts would have been reduced had the impact of CAA benefits been included in the macroeconomic modeling exercise; however, the magnitude of this potential upward bias in the estimate of adverse macroeconomic impact was not quantitatively assessed.

3

Emissions

This chapter presents estimates of emissions reductions due to the Clean Air Act (CAA) for six criteria air pollutants. Reductions are calculated by estimating, on a sector-by-sector basis, the differences in emissions between the control and no-control scenarios. While the relevant years in this analysis are 1970 through 1990, full reporting of emissions was only made for the 1975 to 1990 period since 1970 emission levels are, by assumption, identical for the two scenarios. The criteria pollutants for which emissions are reported in this analysis are: total suspended particulates (TSP),[19] carbon monoxide (CO), volatile organic compounds (VOC), sulfur dioxide (SO_2), nitrogen oxides (NO_x), and Lead (Pb).

The purpose of the present study is to estimate the differences in economic and environmental conditions between a scenario reflecting implementation of historical CAA controls and a scenario which assumes that no additional CAA-related control programs were introduced after 1970. Because of the focus on differences in –rather than absolute levels of– emissions between the scenarios, the various sector-specific emission models were used to estimate both the control and no-control scenario emission inventories. This approach ensures that differences between the scenarios are not distorted by differences between modeled and actual historical emission estimates.[20]

Despite the use of models to estimate control scenario emission inventories, the models used were configured and/or calibrated using historical emissions estimates. The control scenario utility emissions estimates, for example, were based on the ICF CEUM model which was calibrated using historical emissions inventory data.[21] In other cases, such as the EPA Emissions Trends Report (Trends) methodology[22] used to estimate industrial process emissions, historical data were used as the basis for control scenario emissions with little or no subsequent modification. Nevertheless, differences in model selection, model configuration, and macroeconomic input data[23] result in unavoidable, but in this case justifiable, differences between national total historical emission estimates and national total control scenario emission estimates for each pollutant. Comparisons between no-control, control, and official EPA Trends Report historical emissions inventories are presented in Appendix B.[24]

[19] In 1987, EPA replaced the earlier TSP standard with a standard for particulate matter of 10 microns or smaller (PM_{10}).

[20] By necessity, emission models must be used to estimate the hypothetical no-CAA scenario. If actual historical emissions data were adopted for the control scenario, differences between the monitoring data and/or models used to develop historical emission inventories and the models used to develop no-control scenario emission estimates would bias the estimates of the differences between the scenarios.

[21] See ICF Resources, Inc., “Results of Retrospective Electric Utility Clean Air Act Analysis - 1980, 1985 and 1990,” September 30, 1992, Appendix C.

[22] EPA, 1994a: U.S. Environmental Protection Agency, “National Air Pollutant Emission Trends, 1900-1993,” EPA-454/R-94-027, Office of Air Quality Planning and Standards, Research Triangle Park, NC, October 1994.

[23] The Jorgenson/Wilcoxen macroeconomic model outputs were used to configure both the control and no-control scenario emission model runs. While this satisfies the primary objective of avoiding “across model” bias between the scenarios, the macroeconomic conditions associated with the control scenario would not be expected to match actual historical economic events and conditions. To the extent actual historical economic conditions are used to estimate official historical emission inventories, conformity between these historical emissions estimates and control scenario emission estimates would be further reduced.

[24] In general, these comparisons show close correspondence between control scenario and Trends estimates with the largest differences occurring for VOC and CO emissions. The Trends report VOC estimates are generally higher than the control scenario estimates due primarily to the inclusion of Waste Disposal and Recycling as a VOC source in the Trends report. This inconsistency is of no consequence since Waste Disposal and Recycling sources were essentially uncontrolled by the historical CAA and therefore do not appear as a difference between the control and no-control scenarios. The higher CO emission estimates in the Trends Report are primarily associated with higher off-highway vehicle emissions estimates. Again, since off-highway emissions do not change between the control and no-control scenario in the present analysis, this inconsistency is of no consequence.

To estimate no-control scenario emissions, sector-specific historical emissions are adjusted based on changes in the following two factors: (1) growth by sector predicted to occur under the no-control scenario; and (2) the exclusion of controls attributable to specific provisions of the CAA.

To adjust emissions for economic changes under the no-control scenario, activity levels that affect emissions from each sector were identified. These activity levels include, for example, fuel use, industrial activity, and vehicle miles traveled (VMT). The Jorgenson-Wilcoxen (J/W) general equilibrium model was used to estimate changes in general economic conditions, as well as sector-specific economic outcomes used as inputs to the individual sector emission models.[25]

Table 3. Summary of Sector-Specific Emission Modeling Approaches.

Sector	Modeling Approach
On-Highway Vehicles	Modeled using ANL's TEEMS; adjusted automobile emission estimates by changes in personal travel and economic activity in the without CAA case. Truck VMT was obtained from the Federal Highway Administration (FHWA). MOBILE5a emission factors were used to calculate emissions. Lead emission changes from gasoline were estimated by Abt Associates based on historical gasoline sales and the lead content of leaded gasoline in each target year.
Off-Highway Vehicles	ELI analysis based on Trends methods. Recalculated historical emissions using 1970 control efficiencies from Trends. No adjustment was made to activity levels in the without the CAA case.
Electric Utilities	ICF's Coal and Electric Utility Model (CEUM) used to assess SO_2, NO_x, and TSP emission changes. Electricity sales levels were adjusted with results of the J/W model. The Argonne Utility Simulation Model (ARGUS) provided CO and VOC results. Changes in activity levels were adjusted with results of the J/W model. Lead emissions were calculated based on energy consumption data and Trends emission factors and control efficiencies.
Industrial Combustion	ANL industrial boiler analysis for SO_2, NO_x, and TSP using the Industrial Combustion Emissions (ICE) model. VOC and CO emissions from industrial boilers were calculated based on Trends methods; recalculated using 1970 control efficiencies. Lead emissions calculated for boilers and processes based on Trends fuel consumption data, emission factors, and 1970 control efficiencies.
Industrial Processes	ELI analyzed industrial process emissions based on Trends methods. Adjusted historical emissions with J/W sectoral changes in output, and 1970 control efficiencies from Trends. Lead emissions calculated for industrial processes and processes based on Trends fuel consumption data, emission factors, and 1970 control efficiencies.
Commercial / Residential	ANL's Commercial and Residential Simulation System (CRESS) model was used.

[25] For example, the change in distribution of households by income class predicted by the J/W model was used as input to the transportation sector model system. Changes in household income resulted in changes in vehicle ownership and usage patterns which, in turn, influence VMT and emissions. (See Pechan, 1995, p. 43).

The specific outputs from the J/W model used in this analysis are the percentage changes in gross national product (GNP), personal consumption, and output for various economic sectors under the control and no-control scenario for the years 1975, 1980, 1985, and 1990.[26] The sectors for which the results of the J/W model are used include: industrial processes, electric utilities, highway vehicles, industrial boilers, and the commercial/residential sector. For the off-highway sector, economic growth was not taken into account as there was no direct correspondence between J/W sectors and the off-highway vehicle source category activity.

In addition to adjusting for economic activity changes, any CAA-related control efficiencies that were applied to calculate control scenario emissions were removed for the no-control scenario. In most instances, emissions were recalculated based on 1970 control levels.

Uncertainty associated with several key modeling inputs and processes may contribute to potential errors in the emission estimates presented herein. Although the potential errors are likely to contribute in only a minor way to overall uncertainty in the estimated monetary benefits of the Clean Air Act, the most significant emission modeling uncertainties are described at the end of this chapter.

Sector-Specific Approach

The approaches used to calculate emissions for each sector vary based on the complexity of estimating emissions in the absence of CAA controls, taking economic activity levels and CAA regulations into account. For the off-highway vehicle and industrial process sectors, a relatively simple methodology was developed. The approaches used for the highway vehicles, electric utilities, industrial boilers, and commercial/residential sectors were more complex because the J/W model does not address all of the determinants of economic activity in these sectors that might have changed in the absence of regulation. The approaches by sector used to estimate emissions for the two scenarios are summarized in Table 3, and are described in more detail in Appendix B.

Summary of Results

Figure 2 compares the total estimated sulfur dioxide emission from all sectors under the control and no-control scenarios over the period from 1975 to 1990. Figures 3, 4, 5, 6, and 7 provide similar comparisons for NO_x, VOCs, CO, TSP, and Lead (Pb) respectively.

Additional tables presented in Appendix B provide further breakdown of the emissions estimates by individual sector. The essential results are characterized below. For most sectors, emission levels under the control scenario were substantially lower than levels projected under the no-control scenario. For some pollutants, for example NO_x, most of the reductions achieved under the control scenario offset the growth in emissions which would have occurred under the no-control case as a result of increases in population and economic activity. For other pollutants, particularly lead, most of the difference in 1990 emissions projected under the two scenarios reflects significant improvement relative to 1970 emission levels. Appendix B also assesses the consistency of the control and no-control scenario estimates for 1970 to 1990 with pre-1970 historical emissions trends data.

The CAA controls that affected SO_2 emitting sources had the greatest proportional effect on industrial process emissions, which were 60 percent lower in 1990 than they would have been under the no-control scenario. SO_2 emissions from electric utilities and industrial boilers were each nearly 40 percent lower in 1990 as a result of the controls. In terms of absolute tons of emission reductions, controls on electric utilities account for over 10 million of the total 16 million ton difference between the 1990 control and no-control scenario SO_2 emission estimates.

CAA regulation of the highway vehicles sector led to the greatest percent reductions in VOC and NO_x. Control scenario emissions of these pollutants in 1990 were 66 percent and 47 percent lower, respectively, than the levels estimated under the no-control scenario. In absolute terms, highway vehicle VOC controls account for over 15 million of the roughly 17 million ton difference in control and no-control scenario emissions.

Differences between control and no-control scenario CO emissions are also most significant for highway vehicles. In percentage terms, highway vehicle CO emissions were 56 percent lower in 1990 under the control scenario than under the no-control scenario. Industrial process CO emission estimates under the control scenario were about half the levels projected under the no-control scenario. Of the roughly 89 mil-

[26] For details regarding the data linkages between the J/W model and the various emission sector models, see Pechan (1995).

Figure 2. Control and No-control Scenario Total SO_2 Emission Estimates.

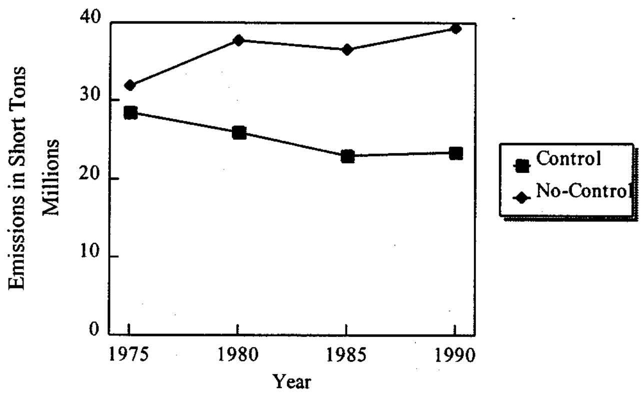


Figure 3. Control and No-control Scenario Total NO_X Emission Estimates.

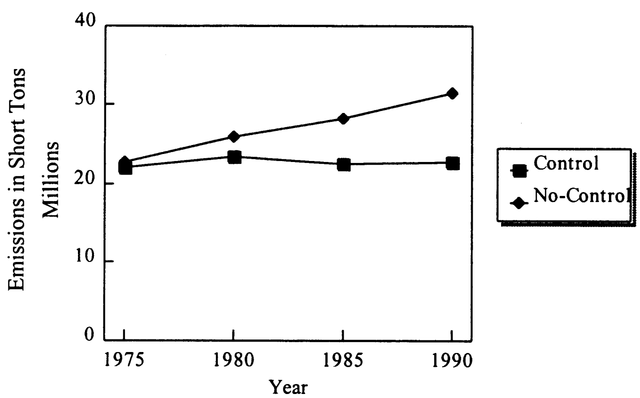


Figure 4. Control and No-control Scenario Total VOC Emission Estimates.

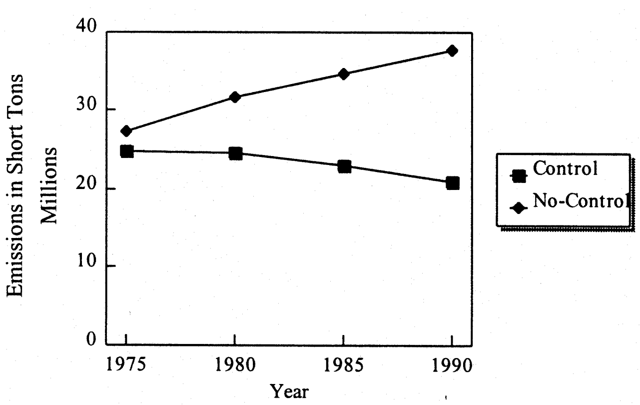


Figure 5. Control and No-control Scenario Total CO Emission Estimates.

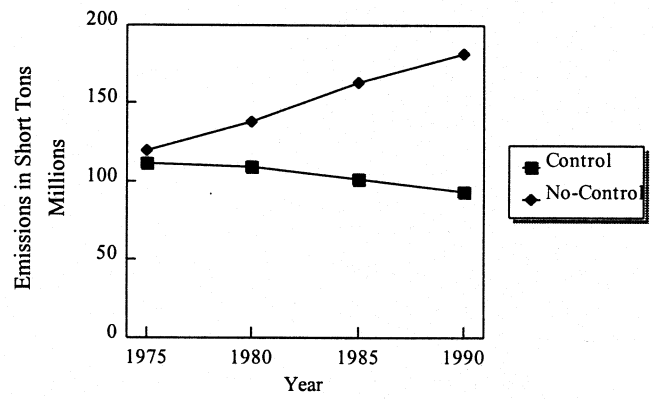


Figure 6. Control and No-control Scenario Total TSP Emission Estimates.

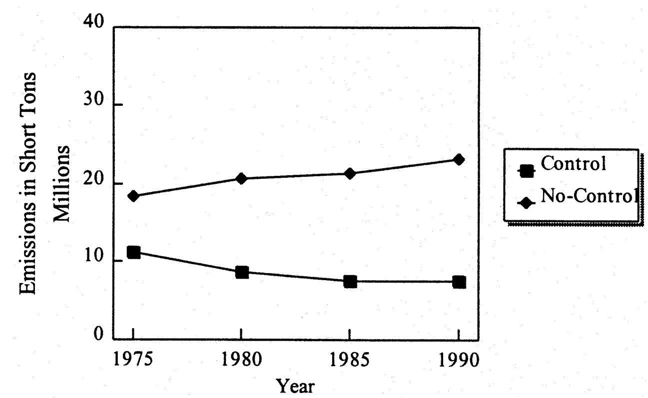
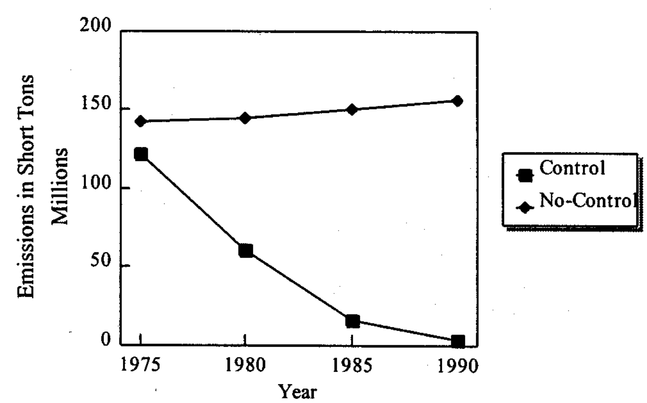


Figure 7. Control and No-control Scenario Total Pb Emission Estimates.



lion ton difference in CO emissions between the two scenarios, 84 million tons are attributable to highway vehicle controls and the rest is associated with reductions from industrial process emissions.

For TSP, the highest level of reductions on a percentage basis was achieved in the electric utilities sector. TSP emissions from electric utilities were 93 percent lower in 1990 under the control scenario than projected under the no-control scenario. TSP emissions from industrial processes were also significantly lower on a percentage basis under the control scenario, with the differential reaching 76 percent by 1990.

This is not an unexpected result as air pollution control regulations in the 1970's focused on solving the visible particulate problems from large fuel combustors. In terms of absolute tons, electric utilities account for over 5 million of the 16 million ton difference between the two scenarios and industrial processes account for almost 10 million tons.

The vast majority of the difference in lead emissions under the two scenarios is attributable to reductions in burning of leaded gasoline. By 1990, reductions in highway vehicle emissions account for 221 thousand of the total 234 thousand ton difference in lead emissions. As shown in more detail in Appendix B, airborne lead emissions from all sectors were virtually eliminated by 1990.

As described in the following chapter and in Appendix C, these emissions inventories were used as inputs to a series of air quality models. These air quality models were used to estimate air quality conditions under the control and no-control scenarios.

Uncertainty in the Emissions Estimates

The emissions inventories developed for the control and no-control scenarios reflect at least two major sources of uncertainty. First, potential errors in the macroeconomic scenarios used to configure the sector-specific emissions model contribute to uncertainties in the emissions model outputs. Second, the emissions models themselves rely on emission factors, source allocation, source location, and other parameters which may be erroneous.

An important specific source of potential error manifest in the present study relates to hypothetical emission rates from various sources under the no-control scenario. Emission rates from motor vehicles, for example, would have been expected to change during the 1970 to 1990 period due to technological changes not directly related to implementation of the Clean Air Act (e.g., advent of electronic fuel injection, or EFI). However, the lack of emissions data from vehicles with EFI but without catalytic converters compelled the Project Team to use 1970 emission factors throughout the 1970 to 1990 period for the no-control scenario. Although this creates a potential bias in the emissions inventories, the potential errors from this and other uncertainties in the emissions inventories are considered unlikely to contribute significantly to overall uncertainty in the monetary estimates of Clean Air Act benefits. This conclusion is based on the demonstrably greater influence on the monetary benefit estimates of uncertainties in other analytical components (e.g., concentration-response functions). A list of the most significant potential errors in the emissions modeling, and their significance relative to overall uncertainty in the monetary benefit estimate, is presented in Table 4.

Table 4. Uncertainties Associated with Emissions Modeling.

Potential Source of Error	Direction of Potential Bias in Estimate of Emission Reduction Benefits	Significance Relative to Key Uncertainties in Overall Monetary Benefit Estimate
Use of 1970 motor vehicle emission factors for no-control scenario without adjustment for advent of Electronic Fuel Injection (EFI) and Electronic Ignition (EI).	Overestimate.	Unknown, but likely to be minor due to overwhelming significance of catalysts in determining emission rates.
Use of ARGUS for utility CO and VOC rather than CEUM.	Unknown.	Negligible.
Use of historical fuel consumption to estimate 1975 SO_2, NO_x, TSP utility emissions.	Unknown.	Negligible.
Adoption of assumption that utility unit inventories remain fixed between the control and no-control scenarios.	Overestimate.	Unknown, but likely to be small since the CAA had virtually no effect on costs of new coal-fired plants built prior to 1975 and these plants comprise a large majority of total coal-fired capacity operating in the 1970 to 1990 period. (See ICF CEUM Report, p. 7).

4

Air Quality

Air quality modeling is the crucial analytical step which links emissions to changes in atmospheric concentrations of pollutants which affect human health and the environment. It is also one of the more complex and resource-intensive steps, and contributes significantly to overall uncertainty in the bottom-line estimate of net benefits of air pollution control programs. The assumptions required to estimate hypothetical no-control scenario air quality conditions are particularly significant sources of uncertainty in the estimates of air quality change, especially for those pollutants which are not linearly related to changes in associated emissions. Specific uncertainties are described in detail at the end of this chapter.

The key challenges faced by air quality modelers attempting to translate emission inventories into air quality measures involve modeling of pollutant dispersion and atmospheric transport, and modeling of atmospheric chemistry and pollutant transformation. These challenges are particularly acute for those pollutants which, rather than being directly emitted, are formed through secondary formation processes. Ozone is the paramount example since it is formed in the atmosphere through complex, nonlinear chemical interactions of precursor pollutants, particularly volatile organic compounds (VOCs) and nitrogen oxides (NO_x). In addition, atmospheric transport and transformation of gaseous sulfur dioxide and nitrogen oxides to particulate sulfates and nitrates, respectively, contributes significantly to ambient concentrations of fine particulate matter. In addition to managing the complex atmospheric chemistry relevant for some pollutants, air quality modelers also must deal with uncertainties associated with variable meteorology and the spatial and temporal distribution of emissions.

Given its comprehensive nature, the present analysis entails all of the aforementioned challenges, and involves additional complications as well. For many pollutants which cause a variety of human health and environmental effects, the concentration-response functions which have been developed to estimate those effects require, as inputs, different air quality indicators. For example, adverse human health effects of particulate matter are primarily associated with the respirable particle fraction;[27] whereas household soiling is a function of total suspended particulates, especially coarse particles. It is not enough, therefore, to simply provide a single measure of particulate matter air quality. Even for pollutants for which particle size and other characteristics are not an issue, different air quality indicators are needed which reflect different periods of cumulative exposure (i.e., “averaging periods”). For example, 3-month growing season averages are needed to estimate effects of ozone on yields of some agricultural crops, whereas adverse human health effect estimates require ozone concentration profiles based on a variety of short-term averaging periods.[28]

Fortunately, in responding to the need for scientifically valid and reliable estimation of air quality changes, air quality modelers and researchers have developed a number of highly sophisticated atmospheric dispersion and transformation models. These models have been employed for years supporting the development of overall federal clean air programs, national assessment studies, State Implementation Plans (SIPs), and individual air toxic source risk assessments. Some of these models, however, require massive amounts of computing power. For example, completing the 160 runs of the Regional Acid Deposition Model (RADM) required for the present study required approximately 1,080 hours of CPU time on a Cray-YMP supercomputer at EPA’s Bay City Supercomputing Center.

Given the resource-intensity of many state-of-the-art models, the Project Team was forced to make difficult choices regarding where to invest the limited

[27] Particles with an aerometric diameter of less than or equal to 10 microns.

[28] For example, ozone concentration-response data exists for effects associated with 1-hour, 2.5-hour, and 6.6-hour exposures.

resources available for air quality modeling. With a mandate to analyze all of the key pollutants affected by historical Clean Air Act programs, to estimate all of the significant endpoints associated with those pollutants, and to do so for a 20 year period covering the entire continental U.S., it was necessary to use simplified approaches for most of the pollutants to be analyzed. In several cases related to primary emissions —particularly sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon monoxide (CO)— simple "roll-up model" strategies were adopted based on the expectation that changes in emissions of these pollutants would be highly correlated with subsequent changes in air quality.[29] Significant pollutants involving secondary atmospheric formation, nonlinear formation mechanisms, and/or long-range transport were analyzed using the best air quality model which was affordable given time and resource limitations. These models, discussed in detail in Appendix C, included the Ozone Isopleth Plotting with Optional Mechanism-IV (OZIPM4) model for urban ozone; various forms of the above-referenced RADM model for background ozone, acid deposition, sulfate, nitrate, and visibility effects in the eastern U.S.; and the SJVAQS/AUSPEX Regional Modeling Adaptation Project (SARMAP) Air Quality Model (SAQM) for rural ozone in California agricultural areas. In addition, a linear scaling approach was developed and implemented to estimate visibility changes in large southwestern U.S. urban areas.

By adopting simplified approaches for some pollutants, the air quality modeling step adds to the overall uncertainties and limitations of the present analysis. The limited expanse and density of the U.S. air quality monitoring network and the limited coverage by available air quality models of major geographic areas[30] further constrain the achievable scope of the present study. Under these circumstances, it is important to remember the extent and significance of gaps in geographic coverage for key pollutants when considering the overall results of this analysis. Key uncertainties are summarized at the end of this chapter in Table 5. More extensive discussion of the caveats and uncertainties associated with the air quality modeling step is presented in Appendix C. In addition, information regarding the specific air quality models used, the characteristics of the historical monitoring data used as the basis for the control scenario profiles, pollutant-specific modeling strategies and assumptions, references to key supporting documents, and important caveats and uncertainties are also presented in Appendix C.

General Methodology

The general methodological approach taken in this analysis starts with the assumption that actual historical air quality will be taken to represent the control scenario. This may seem somewhat inconsistent with the approach taken in earlier steps of the analysis, which used modeled macroeconomic conditions as the basis for estimating macroeconomic effects and emissions. However, the central focus of the overall analysis is to estimate the difference in cost and benefit outcomes between the control and no-control scenarios. It is consistent with this central paradigm to use actual historical air quality data as the basis for estimating how air quality might have changed in the absence of the Clean Air Act.

The initial step, then, for each of the five non-lead (Pb) criteria pollutants[31] was to compile comprehensive air quality profiles covering the entire analytical period from 1970 to 1990. The source for these data was EPA's Aerometric Information Retrieval System (AIRS), which is a publicly accessible database of historical air quality data. The vast number of air quality observations occurring over this twenty year period from the thousands of monitors in the U.S. indicates the need to represent these observations by statistical distributions. As documented in detail in the supporting documents covering SO_2, NO_x, CO, and ozone,[32] both lognormal and gamma distributional forms were tested against actual data to determine the

[29] It is important to emphasize that the correlation expected is between changes in emissions and changes in air quality. Direct correlations between the absolute emissions estimates and empirical air quality measurements used in the present analysis may not be strong due to expected inconsistencies between the geographically local, monitor-proximate emissions densities affecting air quality data.

[30] For example, the regional oxidant models available for the present study do not cover some key Midwestern states, where human health, agricultural crop, and other effects from ozone may be significant.

[31] Lead (Pb), the sixth criteria pollutant, is analyzed separately. The ability to correlate emissions directly with blood lead levels obviates the need for using air quality modeling as an intermediate step toward estimation of exposure.

[32] See SAI SO_2, NO_x, and CO Report (1994) and SAI Ozone Report (1995).

form which provided the best fit to the historical data.[33] Based on these tests, one or the other statistical distribution was adopted for the air quality profiles developed for each pollutant. In addition to reducing the air quality data to a manageable form, this approach facilitated transformations of air quality profiles from one averaging period basis to another.

Once the control scenario profiles based on historical data were developed, no-control scenarios were derived based on the results of the various air quality modeling efforts. Again, the focus of the overall analysis is to isolate the difference in outcomes between the control and no-control scenarios. The no-control scenario air quality profiles were therefore derived by adjusting the control scenario profiles upward (or downward) based on an appropriate measure of the difference in modeled air quality outcomes. To illustrate this approach, consider a simplified example where the modeled concentration of Pollutant A under the no-control scenario is 0.12 ppm, compared to a modeled concentration under the control scenario of 0.10 ppm. An appropriate measure of the difference between these outcomes, whether it is the 0.02 ppm difference in concentration or the 20 percent percentage differential, is then used to ratchet up the control case profile to derive the no-control case profile. Generally, the modeled differential is applied across the entire control case profile to derive the no-control case profile. As described below in the individual sections covering particulate matter and ozone, however, more refined approaches are used where necessary to take account of differential outcomes for component species (i.e., particulate matter), long-range transport, and background levels of pollutants.

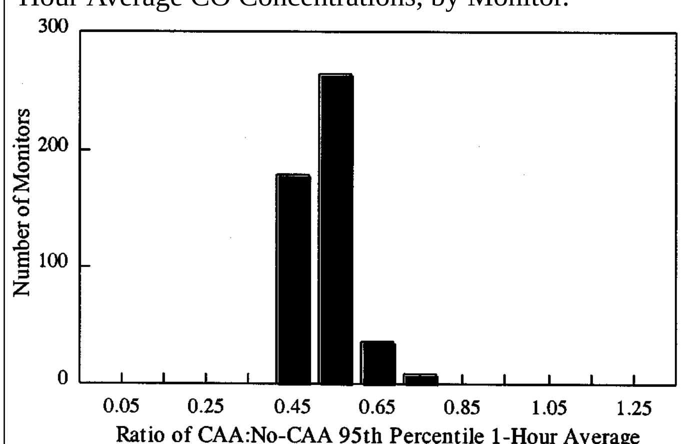
Sample Results

The results of the air quality modeling effort include a vast array of monitor-specific air quality profiles for particulate matter (PM_{10} and TSP),[34] SO_2, NO_2, NO, CO, and ozone; RADM grid cell-based estimates of sulfur and nitrogen deposition; and estimates of visibility degradation for eastern U.S. RADM grid cells and southwestern U.S. urban areas. All of these data were transferred to the effects modelers for use in configuring the human health, welfare, and ecosystem physical effects models. Given the massive quantity and intermediate nature of the air quality data, they are not exhaustively reported herein.[35] To provide the reader with some sense of the magnitude of the difference in modeled air quality conditions under the control and no-control scenarios, some illustrative results for 1990 are presented in this chapter and in Appendix C. In addition, maps depicting absolute levels of control and no-control scenario acid deposition and visibility are presented to avoid potential confusion which might arise through examination of percent change maps alone.[36]

Carbon Monoxide

Figure 8 provides an illustrative comparison of 1990 control versus no-control scenario CO concentrations, expressed as a frequency distribution of the ratios of 1990 control to no-control scenario 95th percentile 1-hour average concentrations at individual CO monitors. Consistent with the emission changes underlying these air quality results, CO concentrations under the control scenario tend to be about half those projected under the no-control scenario, with most individual monitor ratios ranging from about 0.40 to 0.60 percent, and a few with ratios in the 0.60 to 0.80 range.

Figure 8. Frequency Distribution of Estimated Ratios for 1990 Control to No-control Scenario 95th Percentile 1-Hour Average CO Concentrations, by Monitor.



[33] The statistical tests used to determine goodness of fit are described in the SAI reports.

[34] PM data are reported as county-wide values for counties with PM monitors and a sufficient number of monitor observations.

[35] The actual air quality profiles, however, are available on disk from EPA. See Appendix C for further information.

[36] Large percentage changes can result from even modest absolute changes when they occur in areas with good initial (e.g., control scenario) air quality. Considering percentage changes alone might create false impressions regarding absolute changes in air quality in some areas. For example, Appendix C discusses in detail two such cases: the Upper Great Lakes and Florida-Southeast Atlantic Coast areas, which show high percentage changes in sulfur deposition and visibility.

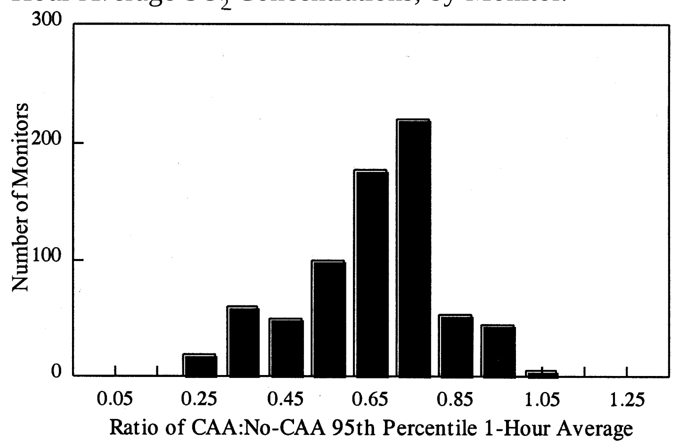
In considering these results, it is important to note that CO is essentially a “hot spot” pollutant, meaning that higher concentrations tend to be observed in localized areas of relatively high emissions. Examples of such areas include major highways, major intersections, and tunnels. Since CO monitors tend to be located in order to monitor the high CO concentrations observed in such locations, one might suspect that using state-wide emissions changes to scale air quality concentration estimates at strategically located monitors might create some bias in the estimates. However, the vast majority of ambient CO is contributed from on-highway vehicles. In addition, the vast majority of the change in CO emissions between the control and no-control scenario occurs due to catalyst controls on highway vehicles. Since CO hot spots result primarily from highway vehicles emissions, controlling such vehicles would mean CO concentrations would be commensurately lowered at CO monitors. While variability in monitor location relative to actual hot spots and other factors raise legitimate concerns about assuming ambient concentrations are correlated with emission changes at any given monitor, the Project Team believes that the results observed provide a reasonable characterization of the aggregate change in ambient CO concentrations between the two scenarios.

Sulfur Dioxide

As for CO, no-control scenario SO_2 concentrations were derived by scaling control scenario air quality profiles based on the difference in emissions predicted under the two scenarios. Unlike CO, SO_2 is predominantly emitted from industrial and utility sources. This means that emissions, and the changes in emissions predicted under the two scenarios, will tend to be concentrated in the vicinity of major point sources. Again, while state-wide emissions changes are used to scale SO_2 concentrations between the scenarios, these state-wide emission changes reflect the controls placed on these individual point sources. Therefore, the Project Team again considers the distribution of control to no-control ratios to be a reasonable characterization of the aggregate results despite the uncertainties associated with estimation of changes at individual monitors.

Figure 9 provides a histogram of the predicted control to no-control ratios for SO_2 which is similar to the one presented for CO. The results indicate that, on an overall basis, SO_2 concentrations were reduced by about one-third. The histogram also shows a much wider distribution of control to no-control ratios for individual monitors than was projected for CO. This result reflects the greater state to state variability in SO_2 emission changes projected in this analysis. This greater state to state variability in turn is a function of the variable responses of SO_2 point sources to historical C control requirements.[37] This source-specific variability was not observed for CO because controls were applied relatively uniformly on highway vehicles.

Figure 9. Frequency Distribution of Estimated Ratios for 1990 Control to No-control Scenario 95th Percentile 1-Hour Average SO_2 Concentrations, by Monitor.

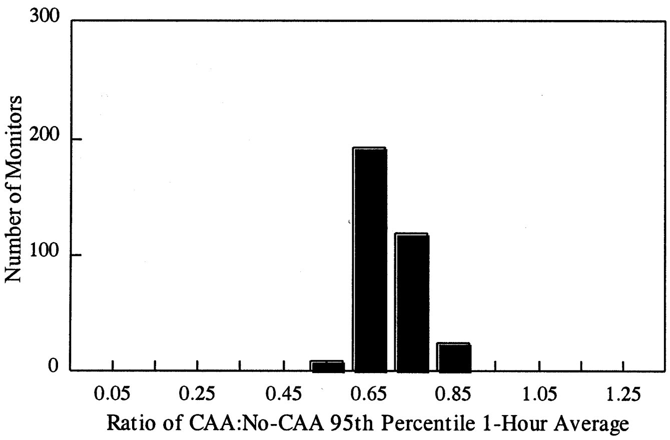


Nitrogen Dioxide

Results for NO_2 are presented in Figure 10. These results are similar to the results observed for CO, and for a similar reason: the vast majority of change in NO_2 emissions between the two scenarios is related to control of highway vehicle emissions. While baseline emissions of NO_2 from stationary sources may be significant, these sources were subject to minimal controls during the historical period of this analysis. On an aggregated basis, overall NO_2 concentrations are estimated to be roughly one-third lower under the control scenario than under the no-control scenario.

[37] Figure 9 indicates that six monitors were projected to have higher SO_2 concentrations for 1990 under the control scenario than under the no-control scenario. All six of these monitors are located in Georgia, a state for which higher 1990 utility SO_2 emissions are projected in the control scenario due to increased use of higher-sulfur coal. The projected increase in overall Georgia utility consumption of higher sulfur coal under the control case is a result of increased competition for the low-sulfur southern Appalachian coal projected to occur under the control scenario.

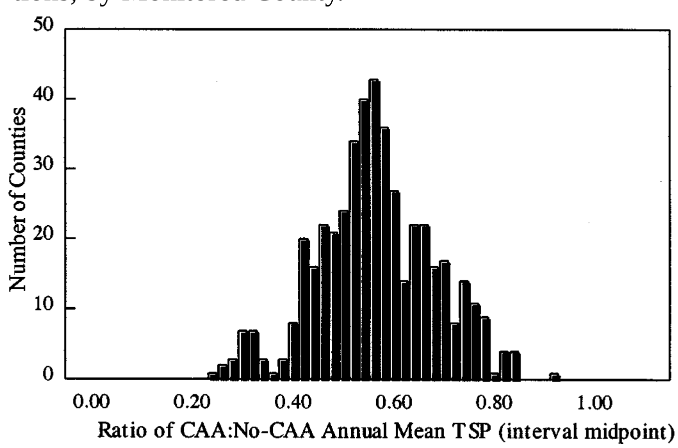
Figure 10. Frequency Distribution of Estimated Ratios for 1990 Control to No-control Scenario 95th Percentile 1-Hour Average NO_2 Concentrations, by Monitor.



Particulate Matter

An indication of the difference in outcomes for particulate matter between the two scenarios is provided by Figure 11. This graph shows the distribution of control to no-control ratios for annual mean TSP in 1990 for those counties which both had particulate monitors and a sufficient number of observations from those monitors.[38] While the distribution of results is relatively wide, reflecting significant county to county variability in ambient concentration, on a national aggregate basis particulate matter concentrations under the control scenario were just over half the level projected under the no-control scenario. The significant county to county variability observed in this case reflects point source-specific controls on particulate matter precursors, especially SO_2, and the effects of long-range transport and transformation.

Figure 11. Frequency Distribution of Estimated Ratios for 1990 Control to No-control Annual Mean TSP Concentrations, by Monitored County.

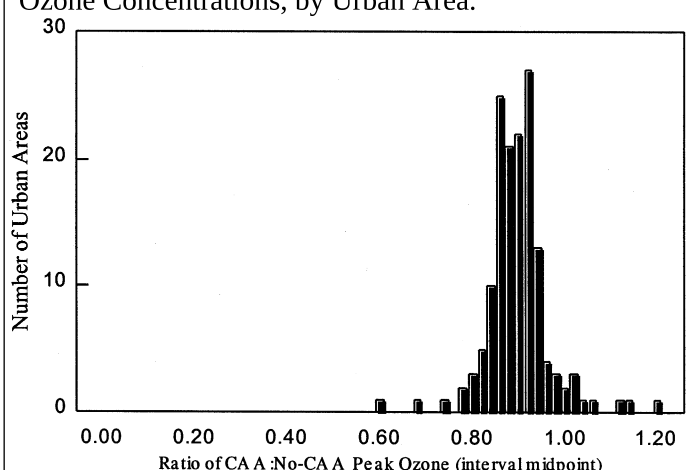


Ozone

Urban Ozone

Figure 12 presents a summary of the results of the 1990 OZIPM4 ozone results for all 147 of the modeled urban areas. In this case, the graph depicts the distribution of ratios of peak ozone concentrations estimated for the control and no-control scenarios. While the vast majority of simulated peak ozone concentration ratios fall below 1.00, eight urban areas show lower simulated peak ozone for the no-control scenario than for the control scenario. For these eight urban areas, emissions of precursors were higher under the no-control scenario; however, the high proportion of ambient NO_x compared to ambient non-methane organic compounds (NMOCs) in these areas results in a decrease in net ozone production in the vicinity of the monitor when NO_x emissions increase.[39]

Figure 12. Distribution of Estimated Ratios for 1990 Control to No-control OZIPM4 Simulated 1-Hour Peak Ozone Concentrations, by Urban Area.



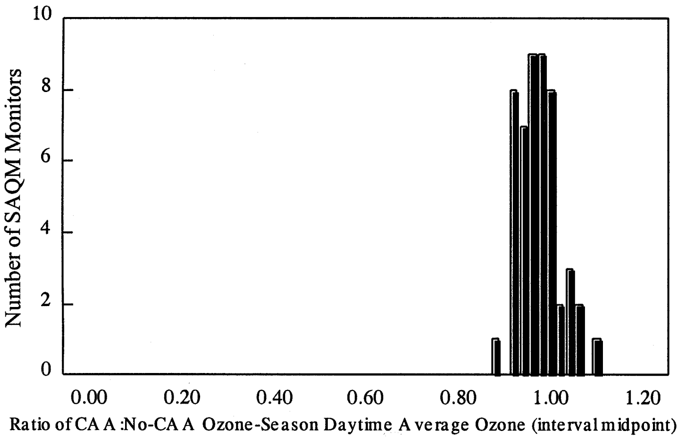
[38] Given the relative importance of particulate matter changes to the bottom line estimate of CAA benefits, and the fact that a substantial portion of the population lives in unmonitored counties, a methodology was developed to allow estimation of particulate matter benefits for these unmonitored counties. This methodology was based on the use of regional air quality modeling to interpolate between monitored counties. It is summarized in Appendix C and described in detail in the SAI PM Interpolation Report (1996).

[39] Over an unbounded geographic area, NO_x reductions generally decrease net ozone production.

Rural Ozone

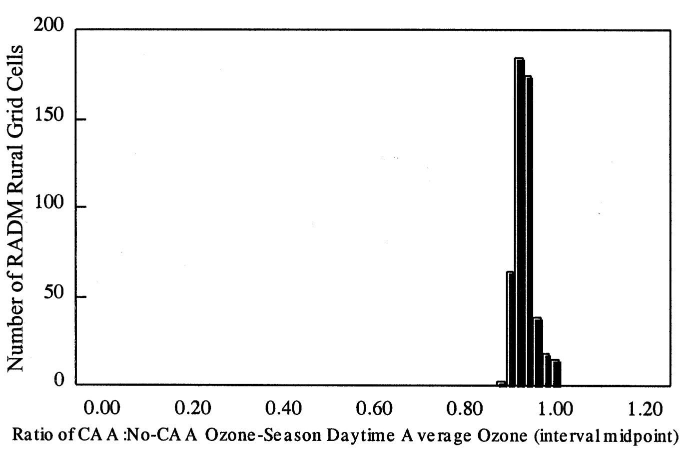
Figures 13 and 14 present frequency distributions for control to no-control ratios of average ozone-season daytime ozone concentrations at rural monitors as simulated by SAQM and RADM, respectively.

Figure 13. Distribution of Estimated Ratios for 1990 Control to No-control SAQM Simulated Daytime Average Ozone Concentrations, by SAQM Monitor.



Both the RADM and SAQM results indicate relatively little overall change in rural ozone concentrations. This is primarily because reductions in ozone precursor emissions were concentrated in populated areas.

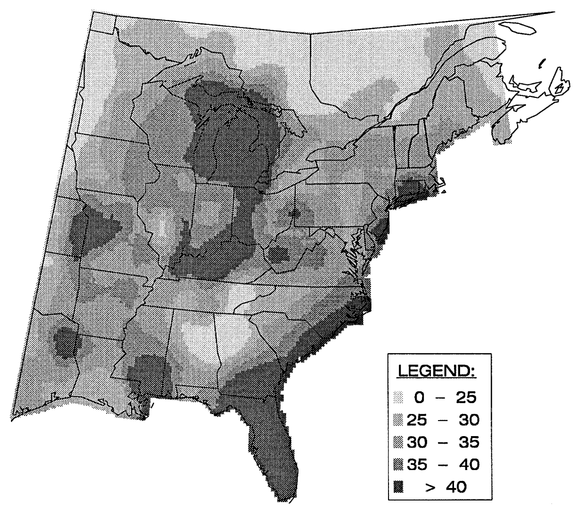
Figure 14. Distribution of Estimated Ratios for 1990 Control to No-control RADM Simulated Daytime Average Ozone Concentrations, by RADM Grid Cell.



Acid Deposition

Figure 15 is a contour map showing the estimated percent increase in sulfur deposition under the no-control scenario relative to the control scenario for 1990. Figure 16 provides comparable information for nitrogen deposition.

Figure 15. RADM-Predicted Percent Increase in Total Sulfur Deposition (Wet + Dry) Under the No-control Scenario.



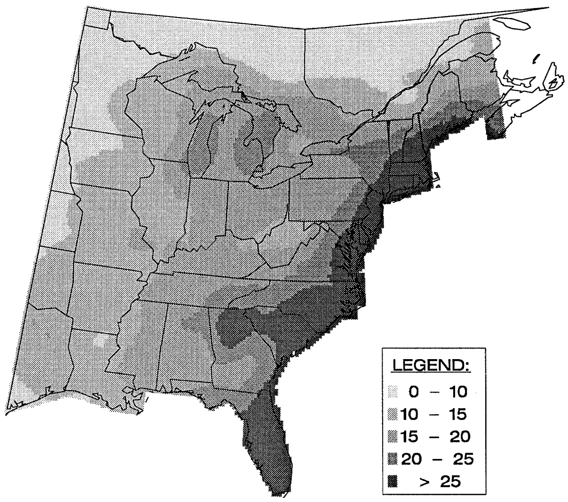
These results show that acid deposition rates increase significantly under the no-control scenario, particularly in the Atlantic Coast area and in the vicinity of states for which relatively large increases in emissions are projected under the no-control scenario (i.e., Kentucky, Florida, Michigan, Mississippi, Connecticut, and Florida).

In the areas associated with large increases in sulfur dioxide emissions, rates of sulfur deposition increase to greater than or equal to 40 percent. The high proportional increase in these areas reflects both the significant increase in acid deposition precursor emissions in upwind areas and the relatively low deposition rates observed under the control scenario.[40]

Along the Atlantic Coast, 1990 nitrogen deposition rates increase by greater than or equal to 25 percent under the no-control scenario. This is primarily due to the significant increase in mobile source nitrogen oxide emissions along the major urban corridors of the eastern seaboard.

[40] Even small changes in absolute deposition can yield large percentage changes when initial absolute deposition is low. See Appendix C for further discussion of this issue.

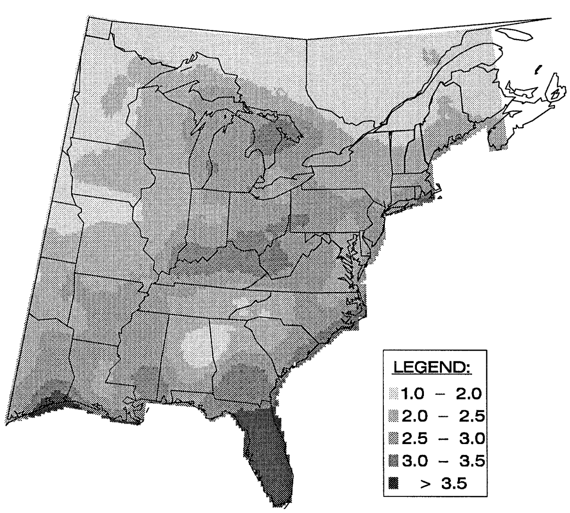
Figure 16. RADM-Predicted Percent Increase in Total Nitrogen Deposition (Wet + Dry) Under the No-control Scenario.



Visibility

The difference in modeled 1990 control and no-control scenario visibility conditions projected by the RADM/EM for the eastern U.S. is depicted by the contour map presented in Figure 17. This figure shows the increase in modeled annual average visibility degradation, in DeciView[41] terms, for 1990 when moving from the control to the no-control scenario. Since the DeciView metric is based on perceptible changes in visibility, these results indicate noticeable deterioration of visibility in the eastern U.S. underthe no-control scenario.

Figure 17. RADM-Predicted Percent Increase in Visibility Degradation, Expressed in DeciViews, for Poor Visibility Conditions (90th Percentile) Under the No-control Scenario.



Visibility changes in 30 southwestern U.S. urban areas were also estimated using emissions scaling techniques. This analysis also found significant, perceptible changes in visibility between the two scenarios. Details of this analysis, including the specific outcomes for the 30 individual urban areas, are presented in Appendix C.

Uncertainty in the Air Quality Estimates

Uncertainty prevades the projected changes in air quality presented in this study. These uncertainties arise due to potential inaccuracies in the emissions inventories used as air quality modeling inputs and due to potential errors in the structure and parameterization of the air quality models themselves. In addition, an important limitation of the present study is the lack of available data and/or modeling results for some pollutants in some regions of the country (e.g., visibility changes in western U.S. Class I areas such as the Grand Canyon). The inability to provide comprehensive estimates of changes in air quality due to the Clean Air Act creates a downward bias in the monetary benefit estimates.

The most important specific sources of uncertainty are presented in Table 5, and are described further in Appendix C. While the list of potential errors presented in Table 5 is not exhaustive, it incorporates the uncertainties with the greatest potential for contributing to error in the monetary benefit estimates. Overall, the uncertainties in the estimated change in air quality are considered small relative to uncertainties contributed by other components of the analysis.

[41] The DeciView Haze Index (dV) is a relatively new visibility indicator aimed at measuring visibility changes in terms of human perception. It is described in detail in Appendix C.

Table 5. Key Uncertainties Associated with Air Quality Modeling.

Potential Source of Error	Direction of Potential Bias in Estimate of Air Quality Benefits	Significance Relative to Key Uncertainties in Overall Monetary Benefit Estimate
Use of OZIPM4 model, which does not capture long-range and night-time transport of ozone. Use of a regional oxidant model, such as UAM-V, would mitigate errors associated with neglecting transport.	Underestimate.	Significant, but probably not major. Overall average ozone response of 15% to NO_x and VOC reductions of approximately 30% and 45%, respectively. Even if ozone response doubled to 30%, estimate of monetized benefits of CAA will not change very much. Significant benefits of ozone reduction, however, could not be monetized.
Use of early biogenic emission estimates in RADM to estimate rural ozone changes in the eastern 31 states.	Underestimate.	Probably minor. Errors are estimated to be within -15% to +25% of the ozone predictions.
Use of proxy pollutants to scale up some particulate species in some areas. Uncertainty is created to the extent species of concern are not perfectly correlated with the proxy pollutants.	Unknown.	Potentially significant. Given the relative importance of the estimated changes in fine particle concentrations to the monetized benefit estimate, any uncertainty associated with fine particles is potentially significant. However, the potential error is mitigated to some extent since proxy pollutant measures are applied to both scenarios.
Use of state-wide average emission reductions to configure air quality models. In some cases, control programs may have been targeted to problem areas, so using state-wide averages would miss relatively large reductions in populated areas.	Underestimate.	Probably minor.
Exclusion of visibility benefits in Class I areas in the Southwestern U.S.	Underestimate.	Probably minor. No sensitivity analysis has been performed; however, monetized benefits of reduced visibility impairment in the Southwest would probably not significantly alter the estimate of monetized benefits.

Table 5 (con't). Key Uncertainties Associated with Air Quality Modeling.

Potential Source of Error	**Direction of Potential Bias in Estimate of Air Quality Benefits**	**Significance Relative to Key Uncertainties in Overall Monetary Benefit Estimate**
Lack of model coverage in western 17 states for acid deposition.	Underestimate.	Probably minor. No sensitivity analysis has been performed; however, monetized benefits of reduced acid deposition in the 17 western states would probably not significantly alter the estimate of monetized benefits.
Use of spatially and geographically aggregated emissions data to configure RADM. Lack of available day-specific meteorological data results in inability to account for temperature effects on VOCs and effect of localized meteorology around major point sources.	Unknown.	Potentially significant. Any effect which might influence the direction of long-range transport of fine particulates such as sulfates and nitrates could significantly influence the estimates of total monetized benefits of the CAA.
Use of constant concentration for organic aerosols between the two scenarios. Holding organic aerosol concentrations fixed omits the effect of changes in this constituent of fine particulate matter.	Underestimate.	Probably minor, because (a) nitrates were also held fixed and nitrates and organic aerosols move in opposite directions so the exclusion of both mitigates the effect of omitting either, (b) sulfates are by far the dominant species in the eastern U.S., and (c) larger errors would be introduced by using emissions scaling to estimate changes in organic aerosols since a significant fraction of organic aerosols are caused by biogenic gas-phase VOC emissions which do not change between the scenarios.
Unavailability of ozone models for rural areas outside the RADM and SAQM domains.	Underestimate.	Probably minor. Misses potential human health, welfare, and ecological benefits of reducing rural ozone in agricultural and other rural areas; however, ozone changes are likely to be small given limited precursor reductions in rural areas. RADM control:no-control ratios are in fact, relatively small.
Use of peak episode changes to estimate changes in annual distribution of ozone concentration.	Unknown.	Probably minor, particularly since relative changes in ozone concentration between the scenarios were small.

5

Physical Effects

Human Health and Welfare Effects Modeling Approach

This chapter identifies and, where possible, estimates the principal health and welfare benefits enjoyed by Americans due to improved air quality resulting from the CAA. Health benefits have resulted from avoidance of air pollution-related health effects, such as premature mortality, respiratory illness, and heart disease. Welfare benefits accrued where improved air quality averted damage to measurable resources, including agricultural production and visibility. The analysis of physical effects required a combination of three components: air quality, population, and health or welfare effects. As structured in this study, the 3-step process involved (1) estimating changes in air quality between the control and no-control scenarios, (2) estimating the human populations and natural resources exposed to these changed air quality conditions, and (3) applying a series of concentration-response equations which translated changes in air quality to changes in physical health and welfare outcomes for the affected populations.

Air Quality

The Project Team first estimated changes in concentrations of criteria air pollutants between the control scenario, which at this step was based on historical air quality, and the no-control scenario. Air quality improvements resulting from the Act were evaluated in terms of both their temporal distribution from 1970 to 1990 and their spatial distribution across the 48 conterminous United States. Generally, air pollution monitoring data provided baseline ambient air quality levels for the control scenario. Air quality modeling was used to generate estimated ambient concentrations for the no-control scenario. A variety of modeling techniques was applied, depending on the pollutant modeled. These modeling approaches and results are summarized in Chapter 4 and presented in detail in Appendix C.

Population

Health and some welfare benefits resulting from air quality improvements were distributed to individuals in proportion to the reduction in exposure. Predicting individual exposures, then, was a necessary step in estimating health effects. Evaluating exposure changes for the present analysis required not only an understanding of where air quality improved as a result of the CAA, but also how many individuals were affected by varying levels of air quality improvements. Thus, a critical component of the benefits analysis required that the distribution of the U.S. population nationwide be established.

Three years of U.S. Census data were used to represent the geographical distribution of U.S. residents: 1970, 1980, and 1990. Population data was supplied at the census block group level, with approximately 290,000 block groups nationwide. Allocating air quality improvements to the population for the other target years of this study – 1975 and 1985 – necessitated interpolation of the three years of population data. Linear interpolation was accomplished for each block group in order to maintain the variability in growth rates throughout the country.

Health and Welfare Effects

Benefits attributable to the CAA were measured in terms of the avoided incidence of physical health effects and measured welfare effects. To quantify such benefits, it was necessary to identify concentration-response relationships for each effect being considered. As detailed in Appendix D, such relationships were derived from the published science literature. In the case of health effects, concentration-response functions combined the air quality improvement and population distribution data with estimates of the number of fewer individuals that suffer an adverse health effect per unit change in air quality. By evaluating each concentration-response function for every monitored location throughout the country, and aggregating the resulting incidence estimates, it was possible to generate national estimates of incidence under the control and no-control scenarios.

In performing this step of the analysis, the Project Team discovered that it was impossible to estimate all of the health and welfare benefits which have resulted from the Clean Air Act. While scientific information was available to support estimation of some effects, many other important health and welfare effects could not be estimated. Furthermore, even though some physical effects could be quantified, the state of the science did not support assessment of the economic value of all of these effects. Table 6 shows the health effects for which quantitative analysis was prepared, as well as some of the health effects which could not be quantified in the analysis. Table 7 provides similar information for selected welfare effects.

While the 3-step analytical process described above was applied for most pollutants, health effects for lead were evaluated using a different methodology. Gasoline as a source of lead exposure was addressed separately from conventional point sources. Instead of using ambient concentrations of lead resulting from use of leaded gasoline, the concentration-response functions linked changes in lead releases directly to changes in the population's mean blood lead level. The amount of leaded gasoline used each year was directly related to mean blood lead levels using a relationship described in the 1985 Lead Regulatory Impact Analysis (U.S. EPA, 1985). Health effects resulting from exposure to point sources of atmospheric lead, such as industrial facilities, were considered using the air concentration distributions modeled around these point sources. Concentration-response functions were then used to estimate changes in blood lead levels in nearby populations.

Most welfare effects were analyzed using the same basic 3-step process used to analyze health effects, with one major difference in the concentration-response functions used. Instead of quantifying the relationship between a given air quality change and the number of cases of a physical outcome, welfare effects were measured in terms of the avoided resource losses. An example is the reduction in agricultural crop losses resulting from lower ambient ozone concentrations under the control scenario. These agricultural benefits were measured in terms of net economic surplus.

Another important welfare effect is the benefit accruing from improvements in visibility under the control scenario. Again, a slightly different methodological approach was used to evaluate visibility improvements. Visibility changes were a direct output of the models used to estimate changes in air quality.[42] The models provided estimates of changes in light extinction, which were then translated mathematically into various specific measures of perceived visibility change.[43] These visibility change measures were then combined with population data to estimate the economic value of the visibility changes. Other welfare effects quantified in terms of avoided resource losses include household soiling damage by PM_{10} and decreased worker productivity due to ozone exposure. The results of the welfare effects analysis are found in Chapter 6 and in Appendices D and F.

Because of a lack of available concentration-response functions (or a lack of information concerning affected populations), ecological effects were not quantified for this analysis. However, Appendix E provides discussion of many of the important ecological benefits which may have accrued due to historical implementation of the CAA.

Key Analytical Assumptions

Several important analytical assumptions affect the confidence which can be placed in the results of the physical effects analysis. The most important of these assumptions relate to (a) mapping of potentially exposed populations to the ambient air quality monitoring network, (b) choosing among competing scientific studies in developing quantitative estimates of physical effects, (c) quantifying the contribution to analytical uncertainty of within-study variances in effects estimates and, perhaps most important in the context of the present study, (d) estimating particulate matter-related mortality based on the currently available scientific literature.

Because these resultant uncertainties were caused by the inadequacy of currently available scientific information, there is no compelling reason to believe

[42] These models, and the specific visibility changes estimated by these models, are described in summary fashion in the previous chapter and are discussed in detail in Appendix C.

[43] These visibility measures are described in Appendix C.

Table 6. Human Health Effects of Criteria Pollutants.

Pollutant	Quantified Health Effects	Unquantified Health Effects	Other Possible Effects
Ozone	Respiratory symptoms Minor restricted activity days Respiratory restricted activity days Hospital admissions Emergency room visits Asthma attacks Changes in pulmonary function Chronic Sinusitis & Hay Fever	Increased airway responsiveness to stimuli Centroacinar fibrosis Inflammation in the lung	Immunologic changes Chronic respiratory diseases Extrapulmonary effects (e.g., changes in structure, function of other organs) Reduced UV-B exposure attenuation
Particulate Matter/ TSP/ Sulfates	Mortality* Bronchitis - Chronic and Acute Hospital admissions Lower respiratory illness Upper respiratory illness Chest illness Respiratory symptoms Minor restricted activity days All restricted activity days Days of work loss Moderate or worse asthma status (asthmatics)	Changes in pulmonary function	Chronic respiratory diseases other than chronic bronchitis Inflammation in the lung
Carbon Monoxide	Hospital Admissions - congestive heart failure Decreased time to onset of angina	Behavioral effects Other hospital admissions	Other cardiovascular effects Developmental effects
Nitrogen Oxides	Respiratory illness	Increased airway responsiveness	Decreased pulmonary function Inflammation in the lung Immunological changes
Sulfur Dioxide	In exercising asthmatics: Changes in pulmonary function Respiratory symptoms Combined responses of respiratory symptoms and pulmonary function changes		Respiratory symptoms in non-asthmatics Hospital admissions
Lead	Mortality Hypertension Non-fatal coronary heart disease Non-fatal strokes IQ loss effect on lifetime earnings IQ loss effects on special education needs	Health effects for individuals in age ranges other than those studied Neurobehavioral function Other cardiovascular diseases Reproductive effects Fetal effects from maternal exposure Delinquent and anti-social behavior in children	

* This analysis estimates excess mortality using PM as an indicator of the pollutant mix to which individuals were exposed.

Table 7. Selected Welfare Effects of Criteria Pollutants.

Pollutant	Quantified Welfare Effects	Unquantified Welfare Effects
Ozone	Changes in crop yields (for 7 crops) Decreased worker productivity	Changes in other crop yields Materials damage Effects on forests Effects on wildlife
Particulate Matter/ TSP/ Sulfates	Household soiling Visibility	Other materials damage Effects on wildlife
Nitrogen Oxides	Visibility	Crop losses due to acid deposition Materials damage due to acid deposition Effects on fisheries due to acidic deposition Effects on forests
Sulfur Dioxide	Visibility	Crop losses due to acid deposition Materials damage due to acid deposition Effects on fisheries due to acidic deposition Effects on forests

that the results of the present analysis are biased in a particular direction. Some significant uncertainties, however, may have arisen from interpretation of model results, underlying data, and supporting scientific studies. These assumptions and uncertainties are characterized in this report to allow the reader to understand the degree of uncertainty and the potential for misestimation of results. In addition, the overall results are presented in ranges to reflect the aggregate effect of uncertainty in key variables. A quantitative assessment of some of the uncertainties in the present study is presented in Chapter 7. In addition, the key uncertainties in the physical effects modeling step of this analysis are summarized in Table 12 at the end of this chapter. The remainder of this section discusses each of the four critical modeling procedures and associated assumptions.

Mapping Populations to Monitors

The Project Team's method of calculating benefits of air pollution reductions required a correlation of air quality data changes to exposed populations. For pollutants with monitor-level data (i.e., SO_2, O_3, NO_2, CO), it was assumed that all individuals were exposed to air quality changes estimated at the nearest monitor. For PM_{10}, historical air quality data were available at the county level. All individuals residing in a county were assumed to be exposed to that county's PM_{10} air quality.[44]

Many counties did not contain particulate matter air quality monitors or did not have a sufficient number of monitor observations to provide reliable estimates of air quality. For those counties, the Project Team conducted additional analyses to estimate PM_{10} air quality changes during the study period. For counties in the eastern 31 states, the grid cell-specific sulfate particle concentrations predicted by the RADM model were used to provide a scaled interpolation between monitored counties.[45] For counties outside the RADM domain, an alternative method based on state-wide average concentrations was used. With this supplemental analysis, estimates were developed of the health effects of the CAA on almost the entire continental U.S. population.[46] Compliance costs in-

[44] In some counties and in the early years of the study period, particulate matter was monitored as TSP rather than as PM_{10}. In these cases, PM_{10} was estimated by applying TSP:PM_{10} ratios derived from historical data. This methodology is described in Appendix C.

[45] The specific methodology is described in detail in Appendix C.

[46] While this modeling approach captures the vast majority of the U.S. population, it does not model exposure for everyone. To improve computational efficiency, those grid cells with populations less than 500 were not modeled; thus, the analysis covered somewhat more than 97 percent of the population.

curred in Alaska and Hawaii were included in this study, but the benefits of historical air pollution reductions were not. In addition, the CAA yielded benefits to Mexico and Canada that were not captured in this study.

Air quality monitors are more likely to be found in high pollution areas rather than low-pollution areas. Consequently, mapping population to the nearest monitor regardless of the distance to that monitor almost certainly results in an overstatement of health impacts due to air quality changes for those populations. The Project Team conducted a sensitivity analysis to illustrate the importance of the "mapping to nearest monitor" assumption. For comparison to the base case, which modeled exposure for the 48 state population, Table 8 presents the percentage of the total 48-state population covered in the "50 km" sensitivity scenario. For most pollutants in most years, 25 percent or more of the population resided more than 50 km from an air quality monitor (or in a county without PM_{10} monitors). Estimated health benefits are approximately linear to population covered — that is, if the population modeled for a pollutant in a given year in the sensitivity analysis is 25 percent smaller than the corresponding population modeled in the base case, then estimated health benefits are reduced by roughly 25 percent in the sensitivity case. This sensitivity analysis demonstrates that limiting the benefits analysis to reflect only those living within 50 km of a monitor or within a PM-monitored county would lead to a substantial underestimate of the historical benefits of the CAA. Since these alternative results may have led to severely misleading comparisons of the costs and benefits of the Act, the Project Team decided to adopt the full 48-state population estimate as the central case for this analysis despite the greater uncertainties and potential biases associated with estimating exposures from distant monitoring sites.

Table 8. Percent of Population (of the Continental US) within 50km of a monitor (or in a County with PM monitors), 1970-1990.

	Pollutant				
Year	**PM_{10}**	**O_3**	**NO_2**	**SO_2**	**CO**
1975	79%	56%	53%	65%	67%
1980	80%	71%	59%	73%	68%
1985	75%	72%	61%	73%	68%
1990	68%	74%	62%	71%	70%

Choice of Study

The Project Team relied on the most recent available, published scientific literature to ascertain the relationship between air pollution and human health and welfare effects. The choice of studies, and the uncertainties underlying those studies, also created uncertainties in the results. For example, to the extent the published literature may collectively overstate the effects of pollution, EPA's analysis will overstate the effects of the CAA. Such outcomes may occur because scientific research which fails to find significant relationships is less likely to be published than research with positive results. On the other hand, history has shown that it is highly likely that scientific understanding of the effects of air pollution will improve in the future, resulting in discovery of previously unknown effects. Important examples of this phenomenon are the substantial expected health and welfare benefits of reductions in lead and ambient particulate matter, both of which have been shown in recent studies to impose more severe effects than scientists previously believed. To the extent the present analysis misses effects of air pollution that have not yet been subject to adequate scientific inquiry, the analysis may understate the effects of the CAA.

For some health endpoints, the peer-reviewed scientific literature provides multiple, significantly differing alternative CR functions. In fact, it is not unusual for two equally-reputable studies to differ by a factor of three or four in implied health impact. The difference in implied health effects across studies can be considered an indication of the degree of scientific uncertainty associated with measurement of that health effect. Where more than one acceptable study was available, the Project Team used CR functions from all relevant studies to infer health effects. That is, the health effect implied by each study is reported (see Appendix D), and a range of reported results for a particular health endpoint can be interpreted as a measure of the uncertainty of the estimate.

Variance Within Studies

Even where only one CR function was available for use, the uncertainty associated with application of that function to estimate physical outcomes can be evaluated quantitatively. Health effects studies provided "best estimates" of the relationship between air quality changes and health effects, and a measure of the statistical uncertainty of the relationship. In this analysis, the Project Team used simulation modeling techniques to evaluate the overall uncertainty of the results given uncertainties within individual studies, across studies examining a given endpoint, and in the economic valuation coefficients applied to each endpoint. The analysis estimating aggregate quantitative uncertainty is presented in Chapter 7.

PM-Related Mortality

The most serious human health impact of air pollution is an increase in incidences of premature mortality. In the present study, excess premature mortality is principally related to increased exposure to lead (Pb)[47] and to particulate matter (PM) and associated non-Pb criteria pollutants.[48] With respect to PM, a substantial body of published health science literature recognizes a correlation between elevated PM concentrations and increased mortality rates. However, there is a diversity of opinion among scientific experts regarding the reasonableness of applying these studies to derive quantitative estimates of premature mortality associated with exposure to PM. While 19 of 21 members of the Science Advisory Board Clean Air Act Scientific Advisory Committee agree that present evidence warrants concern and implementation of a fine particle ($PM_{2.5}$) standard to supplement the PM_{10} standard, they also point out that the causal mechanism has not been clearly established.

For the purposes of the present study, the Project Team has concluded that the well-established correlation between exposure to elevated PM and premature mortality is sufficiently compelling to warrant an assumption of a causal relationship and derivation of quantitative estimates of a PM-related premature mortality effect. In addition to the assumption of causality, a number of other factors contribute to uncertainty in the quantitative estimates of PM-related mortality.[49] First, although there is uncertainty regarding the shape of the CR functions derived from the epidemiological studies, the present analysis assumes the relationship to be linear throughout the relevant range of exposures. Second, there is significant variability among the underlying studies which may reflect, at least in part, location-specific differences in CR functions. Transferring CR functions derived from one or more specific locations to all other locations may contribute significantly to uncertainty in the effect estimate. Third, a number of potentially significant biases and uncertainties specifically associated with each of the two types of PM-related mortality study further contribute to uncertainty. The remainder of this section discusses these two groups of studies and their attendant uncertainties and potential biases. (See Appendix D for a more complete discussion of these studies and their associated uncertainties.)

Short-Term Exposure Studies

Many of the studies examining the relationship between PM exposure and mortality evaluate changes in mortality rates several days after a period of elevated PM concentrations. In general, significant correlations have been found. These "short-term exposure" or "episodic" studies are unable to address two important issues: (1) the degree to which the observed excess mortalities are "premature," and (2) the degree to which daily mortality rates are correlated with long-term exposure to elevated PM concentrations (i.e., exposures over many years rather than a few days).

Because the episodic mortality studies evaluate the mortality rate impact only a few days after a high-pollution event, it is likely that many of the "excess mortality" cases represented individuals who were already suffering impaired health, and for whom the high-pollution event represented an exacerbation of an already serious condition. Based on the episodic studies only, however, it is unknown how many of the victims would have otherwise lived only a few more days or weeks, or how many would have recovered to enjoy many years of a healthy life in the absence of the high-pollution event. For the purpose of cost-benefit analysis, it can be important to determine whether a pollution event reduces the average lifespan by several days or by many years. Although the episodic mortality studies do not provide an estimate of the expected life years lost (nor do they address the health status of victims), some have evaluated the age of the excess premature mortality cases, and have estimated that 80 to 85 percent of the victims are age 65 or older.

In addition to causing short-term health problems, air pollution (measured by elevated annual PM con-

[47] Detailed information on methods, sources, and results of the Pb mortality analysis are presented in Appendix G.

[48] PM concentrations are highly correlated with concentrations of other criteria pollutants. It is difficult to determine which pollutant is the causative factor in elevated mortality rates. In this study, the Project Team has used PM as a surrogate for a mix of criteria pollutants.

[49] It should also be noted that some of the morbidity studies, most notably the PM/chronic bronchitis epidemiological studies, involve many of the same uncertainties.

centrations) can cause longer-term health problems that may lead to premature mortality. Such long-term changes in susceptibility to premature mortality in the future will be missed by efforts to correlate premature mortalities with near-term episodes of elevated pollution concentrations. Consequently, excess premature mortality estimates based on the results of the "episodic" mortality studies will underestimate the effect of long-term elevated pollution concentrations on mortality rates.

Long-Term Exposure Studies

The other type of PM-related mortality study involves examination of the potential relationship between long-term exposure to PM and annual mortality rates. These studies are able to avoid some of the weaknesses of the episodic studies. In particular, by investigating changes in annual (rather than daily) mortality rates, the long-term studies do not predict most cases of excess premature mortality where mortality is deferred for only a few days; also, the long-term studies are able to discern changes in mortality rates due to long-term exposure to elevated air pollution concentrations. Additionally, the long-term exposure studies are not limited to measuring mortalities that occur within a few days of a high-pollution event. Consequently, use of the results of the long-term studies is likely to result in a more complete assessment of the effect of air pollution on mortality risk.

The long-term exposure studies, however, have some significant limitations and potential biases. Although studies that are well-executed attempt to control for those factors that may confound the results of the study, there is always the possibility of insufficient or inappropriate adjustment for those factors that affect long-term mortality rates and may be confounded with the factor of interest (e.g., PM concentrations). Prospective cohort studies have an advantage over ecologic, or population-based, studies in that they gather individual-specific information on such important risk factors as smoking. It is always possible, however, that a relevant, individual-specific risk factor may not have been controlled for or that some factor that is not individual-specific (e.g., climate) was not adequately controlled for. It is therefore possible that differences in mortality rates that have been ascribed to differences in average PM levels may be due, in part, to some other factor or factors (e.g., differences among communities in diet, exercise, ethnicity, climate, industrial effluents, etc.) that have not been adequately controlled for.

Another source of uncertainty surrounding the prospective cohort studies concerns possible historical trends in PM concentrations and the relevant period of exposure, which is as yet unknown. TSP concentrations were substantially higher in many locations for several years prior to the cohort studies and had declined substantially by the time these studies were conducted. If this is also true for $PM_{2.5}$ and PM_{10}, it is possible that the larger PM coefficients reported by the long-term exposure studies (as opposed to the short-term exposure studies) reflect an upward bias. If the relevant exposure period extends over a decade or more, then a coefficient based on PM concentrations at the beginning of the study or in those years immediately prior to the study could be biased upward if pollution levels had been decreasing markedly for a decade or longer prior to the study.

On the other hand, if a downward trend in PM concentrations continued throughout the period of the study, and if a much shorter exposure period is relevant (e.g., contained within the study period itself), then characterizing PM levels throughout the study by those levels just prior to the study would tend to bias the PM coefficient downward. Suppose, for example, that PM levels were converging across the different study locations over time, and in particular, into the study period. (That is, suppose PM levels were decreasing over time, but decreasing faster in the high-PM locations than in the low-PM locations, so that at the beginning of the study period the interlocational differences in PM concentrations were smaller than they were a decade earlier.) Suppose also that the relevant exposure period is about one year, rather than many years. The Pope study characterizes the long-term PM concentration in each of the study locations by the median PM concentration in the location during the five year period 1979-1983. Study subjects were followed, however, from 1982 through 1989. If the difference in median PM concentrations across the 50 study locations during the period 1979-1983 was greater than the difference during the period 1983-1988, and if it is PM levels during the period 1983-1988 that most affect premature mortality during the study period (rather than PM levels during the period 1979-1983), then the study would have attributed interlocational differences in mortality to larger interlocational differences in PM concentrations than were actually relevant. This would result in a downward bias of the PM coefficient estimated in the study.

The relevant exposure period is one of a cluster of characteristics of the mortality-PM relationship that are as yet unknown and potentially important. It is also unknown whether there is a time lag in the PM effect. Finally, it is unknown whether there may be cumulative effects of chronic exposure — that is, whether the relative risk of mortality actually increases as the period of exposure increases.

Three recent studies have examined the relationship between mortality and long-term exposure to PM: Pope et al. (1995), Dockery et al. (1993), and Abbey et al. (1991). The Pope et al. study is considered a better choice of long-term exposure study than either of the other two studies. Pope et al. examined a much larger population and many more locations than either the Dockery study or the Abbey study. The Dockery study covered only six cities. The Abbey study covered a cohort of only 6,000 people in California. In particular, the cohort in the Abbey study was considered substantially too small and too young to enable the detection of small increases in mortality risk. The study was therefore omitted from consideration in this analysis. Even though Pope et al. (1995) reports a smaller premature mortality response to elevated PM than Dockery et al. (1993), the results of the Pope study are nevertheless consistent with those of the Dockery study.

Pope et al., (1995) is also unique in that it followed a largely white and middle class population, decreasing the likelihood that interlocational differences in premature mortality were attributable to differences in socioeconomic status or related factors. Furthermore, the generally lower mortality rates and possibly lower exposures to pollution among this group, in comparison to poorer minority populations, would tend to bias the PM coefficient from this study downward, counteracting a possible upward bias associated with historical air quality trends discussed above.

Another source of downward bias in the PM coefficient in Pope et al., (1995) is that intercity movement of cohort members was not considered. Migration across study cities would result in exposures of cohort members being more similar than would be indicated by assigning city-specific annual average pollution levels to each member of the cohort. The more intercity migration there is, the more exposure will tend toward an intercity mean. If this is ignored, differences in exposure levels, proxied by differences in city-specific annual average PM levels, will be exaggerated, resulting in a downward bias of the PM coefficient. This is because a given difference in mortality rates is being associated with a larger difference in PM levels than is actually the case.

An additional source of uncertainty in the Pope et al., study arises from the PM indicator used in the study. The Pope et al. study examined the health effects associated with two indices of PM exposure; sulfate particles and fine particles ($PM_{2.5}$). The $PM_{2.5}$ relationship is used in this analysis because it is more consistent with the air quality data selected for this analysis (PM_{10}). Because we use a $PM_{2.5}$ mortality relationship, air quality profiles were developed from the PM_{10} profiles generated for the entire 20 year period. The same regional information about the PM_{10} components (sulfate, nitrate, organic particulate and primary particulate) used to develop the PM_{10} profiles was used to develop regional $PM_{2.5}/PM_{10}$ ratios. Although both urban and rural ratios are available, for computational simplicity, only the regional urban ratios were used to estimate the $PM_{2.5}$ profiles from the PM_{10} profiles used in the analysis. This reflects the exposure of the majority of the modeled population (i.e., the urban population), while introducing some error in the exposure changes for the rural population. In the east and west, where the rural ratio is larger than the urban ratio, the change in $PM_{2.5}$ exposure will be underestimated for the rural population. In the central region the $PM_{2.5}$ change will be overestimated. These ratios were used in each year during 1970-1990, introducing another source of uncertainty in the analysis.

After considering the relative advantages and disadvantages of the various alternative studies available in the peer-reviewed literature, the Project Team decided that the long-term exposure studies were preferable for the purposes of the present study, primarily because the long-term exposure studies appear to provide a more comprehensive estimate of the premature mortality incidences attributable to PM exposure. Among the long-term exposure studies, the Pope et al., (1995) study appears more likely to mitigate a key source of potential confounding. For these reasons, the CR function estimated in Pope et al., (1995) is considered the most reasonable choice for this analysis and is utilized in spite of the several important residual uncertainties and potential biases which are subsequently reflected in the PM-related mortality effect estimate.

Health Effects Modeling Results

This section provides a summary of the differences in health effects estimated under the control and no-control scenarios. Because the differences in air quality between the two scenarios generally increased from 1970 to 1990, and the affected population grew larger during that period, the beneficial health effects of the CAA increased steadily during the 1970 to 1990 period. More detailed results are presented in Appendix D.

Avoided Premature Mortality Estimates

The Project Team determined that, despite their limitations, the long-term particulate matter exposure studies provided the superior basis for estimating mortality effects for the purpose of benefit-cost analysis. Three prospective cohort studies were identified (Pope et al. (1995), Dockery et al. (1993), and Abbey et al. (1991)), although the Abbey study was omitted from consideration because the cohort in that study was considered insufficient to allow the detection of small increases in mortality risk. Exposure-response relationships inferred from the Pope et al. study were used in the health benefits model to estimate avoided mortality impacts of the CAA. The Pope et al. study was selected because it is based on a much larger population and a greater number of communities (50) than is the six-city Dockery et al. Study. The results of the Pope et al. are consistent with those of the other study, and are consistent with earlier ecological population mortality studies. See Appendix D for additional discussion of the selection of mortality effects studies.

Table 9 presents estimated avoided excess premature mortalities for 1990 only, with the mean estimate and 90 percent confidence interval. See Appendix D for more detail on results implied by individual epidemiological studies, and on the temporal pattern of impacts.[50] The model reports a range of results for each health endpoint. Here, the fifth percentile, mean, and ninety-fifth percentile estimates are used to characterize the distribution. The total number of avoided cases of premature mortality due to reduced exposure to lead (Pb) and particulate matter are presented. Additionally, avoided mortality cases are listed by age cohort of those who have avoided premature mortality in 1990, along with the expected remaining lifespan (in years) for the average person in each age cohort. The average expected remaining lifespan across all age groups is also indicated. These averages might be higher if data were available for PM-related mortality in the under 30 age group and for Pb-related mortality in the 5-39 age group.

Table 9. Criteria Pollutants Health Benefits -- Distributions of 1990 Avoided Premature Mortalities (thousands of cases reduced) for 48 State Population.

Pollutant	Age group	Remaining Life Expectancy (yrs)	Annual Cases Avoided (thousands)		
			5th %ile	Mean	95th %ile
$PM_{2.5}$	30 and over		112	184	257
	30-34	48	2	3	5
	35-44	38	5	8	11
	45-54	29	7	11	15
	55-64	21	14	23	33
	65-74	14	26	43	62
	75-84	9	32	54	76
	>84	6	24	41	59
		Avg.: 14*			
Lead	all ages		7	22	54
	infants	75	5	5	5
	40-44	38	0	2	13
	45-54	29	0	4	20
	55-64	21	0	6	18
	65-74	14	0	4	15
		Avg.: 38*			
TOTAL			166	205	252

*Averages calculated from proportions of premature mortalities by age group, from Table D-14.

Non-Fatal Health Impacts

The health benefits model reports non-fatal health effects estimates similarly to estimates of premature mortalities: as a range of estimates for each quantified health endpoint, with the range dependent on the quantified uncertainties in the underlying concentration-response functions. The range of results for 1990 only is characterized in Table 10 with fifth percentile, mean, and ninety-fifth percentile estimates. All estimates are expressed as thousands of new cases avoided in 1990. "Lost IQ Points" represent the aggregate number of points (in thousands) across the population affected by lead concentrations in 1990. All "Hospital Admissions" estimates are in thousands of admissions, regardless of the length of time spent in the hospital. "Shortness of breath" is expressed as thousands of

[50] Earlier years are estimated to have had fewer excess premature mortalities.

Table 10. Criteria Pollutants Health Benefits -- Distributions of 1990 Non-Fatal Avoided Incidence (thousands of cases reduced) for 48 State Population.

Endpoint	Pollutant(s)	Affected Population (age group)	Annual Effects Avoided (thousands) 5th %ile	Mean	95th %ile	Unit
Chronic Bronchitis	PM	all	493	674	886	cases
Lost IQ Points	Lead	children	7,440	10,400	13,000	points
IQ < 70	Lead	children	31	45	60	cases
Hypertension	Lead	men 20-74	9,740	12,600	15,600	cases
Chronic Heart Disease	Lead	40-74	0	22	64	cases
Atherothrombotic brain infarction	Lead	40-74	0	4	15	cases
Initial cerebrovascular accident	Lead	40-47	0	6	19	cases
Hospital Admissions						
All Respiratory	PM & O3	all	75	89	103	cases
COPD + Pneumonia	PM & O3	over 65	52	62	72	cases
Ischemic Heart Disease	PM	over 65	7	19	31	cases
Congestive Heart Failure	PM & CO	65 and over	28	39	50	cases
Other Respiratory-Related Ailments						
Shortness of breath, days	PM	children	14,800	68,800	133,000	days
Acute Bronchitis	PM	children	0	8,700	21,600	cases
Upper & Lower Resp. Symptoms	PM	children	5,400	9,500	13,400	cases
Any of 19 Acute Symptoms	PM & O3	18-65	15,400	130,000	244,000	cases
Asthma Attacks	PM & O3	asthmatics	170	850	1,520	cases
Increase in Respiratory Illness	NO2	all	4,840	9,800	14,000	cases
Any Symptom	SO2	asthmatics	26	264	706	cases
Restricted Activity and Work Loss Days						
MRAD	PM & O3	18-65	107,000	125,000	143,000	days
Work Loss Days (WLD)	PM	18-65	19,400	22,600	25,600	days

The following additional welfare benefits were quantified directly in economic terms: household soiling damage, visibility, decreased worker productivity, and agricultural benefits (measured in terms of net surplus).

days: that is, one "case" represents one child experiencing shortness of breath for one day. Likewise, "Restricted Activity Days" and "Work Loss Days" are expressed in person-days.

Other Physical Effects

Human health impacts of criteria pollutants dominate quantitative analyses of the effects of the CAA, in part because the scientific bases for quantifying air quality and physical effect relationships are most advanced for health effects. The CAA yielded other benefits, however, which are important even though they were sometimes difficult or impossible to quantify fully given currently available scientific and applied economic information.

Ecological Effects

The CAA yielded important benefits in the form of healthier ecological resources, including: stream, river, lake and estuarine ecosystems; forest and wetland ecosystems; and agricultural ecosystems. These benefits are important because of both the intrinsic value of these ecological resources and the intimate linkage between human health and the health and vitality of our sustaining ecosystems. Given the complexity of natural and agricultural ecosystems and the large spatial and temporal dimensions involved, it has been difficult or impossible to quantify benefits fully given currently available scientific and applied economic information.

Aquatic and Forest Effects

Beyond the intrinsic value of preserving natural aquatic (i.e., lakes, streams, rivers, and estuaries), terrestrial (i.e., forest and grassland), and wetland ecosystems and the life they support, protection of ecosystems from the adverse effects of air pollution can yield significant benefits to human welfare. The historical reductions in air pollution achieved under the CAA probably led to significant improvements in the health of ecosystems and the myriad ecological services they provide. Reductions in acid deposition (SO_x and NO_x) and mercury may have reduced adverse effects on aquatic ecosystems, including finfish, shellfish, and amphibian mortality and morbidity, reduced acidification of poorly buffered systems, and reduced eutrophication of estuarine systems. Ecological protection, in turn, can enhance human welfare through improvements in commercial and recreational fishing, wildlife viewing, maintenance of biodiversity, improvements in drinking water quality, and improvements in visibility.

Wetlands ecosystems are broadly characterized as transitional areas between terrestrial and aquatic systems in which the water table is at or near the surface or the land is periodically covered by shallow water. Valuable products and services of wetlands include: flood control, water quality protection and improvement, fish and wildlife habitat, and landscape and biological diversity. High levels of air pollutants have the potential to adversely impact wetlands. Reductions of these pollutants due to compliance with the CAA have reduced the adverse effects of acidification and eutrophication of wetlands, which in turn has protected habitat and drinking water quality.

Forest ecosystems, which cover 33 percent of the land in the United States, provide an extensive array of products and services to humans. Products include lumber, plywood, paper, fuelwood, mulch, wildlife (game), water (quality), seeds, edible products (e.g., nuts, syrup), drugs, and pesticides. Forest services include recreation, biological and landscape diversity, amenity functions (e.g., urban forest), reduced runoff and erosion, increased soil and nutrient conservation, pollutant sequestration (e.g., CO_2, heavy metals) and pollutant detoxification (e.g., organochlorines). The greatest adverse effect on forest systems are imposed by ozone. No studies have attempted to quantify the economic benefits associated with all product and service functions from any U.S. forest. Some studies have attempted to estimate the net economic damage from forest exposure to air pollutants by calculating hypothetical or assumed reductions in growth rates of commercial species. While quantification of forest damages remains incomplete, available evidence suggests that recreational, service, and non-use benefits may be substantial.

For a more comprehensive discussion of the possible ecological effects of the CAA, see Appendix E.

Quantified Agricultural Effects

Quantification of the effects of the CAA on agriculture was limited to the major agronomic crop species including barley, corn, soybeans, peanuts, cotton, wheat, and sorghum. These species account for 70 percent of all cropland in the U.S., and 73 percent of the nation's agricultural receipts. Ozone is the primary pollutant affecting agricultural production. Nationwide crop damages were estimated under the control and no-control scenarios. Net changes in economic surplus (in 1990 dollars) annually and as a cumulative present value (discounted at 5%) over the period 1976-1990 were estimated. Positive surpluses were exhibited in almost all years and were the result of the increase in yields associated with decreased ozone concentrations under the control scenario. The present value (in 1990) of the estimated agricultural benefits of the CAA ranges from $7.8 billion in the minimum response case to approximately $37 billion in the maximum response case[51] (note that discounting 1976-1990 benefits to 1990 amounts to a compounding of benefits). Exposure-response relationships and cultivar mix reflect historical patterns and do not account for possible substitution of more ozone-resistant cultivars in the no-control scenario. Thus, the upper end of the range of benefit calculations may overestimate the actual agricultural benefits of the CAA with respect to these crops. Because numerous crops are excluded from the analysis, including high value crops that may be sensitive to ozone, the lower end of the range is not likely to fully capture the agricultural benefits of reductions in ozone.

Effects of Air Toxics

In addition to control of criteria pollutants, the Clean Air Act resulted in control of some air toxics — defined as non-criteria pollutants which can cause adverse effects to human health and to ecological resources. Control of these pollutants resulted both from incidental control due to criteria pollutant programs and specific controls targeted at air toxics through the National Emission Standards for Hazardous Air Pollutants (NESHAPs) under Section 112 of the Act.

Air toxics are capable of producing a wide variety of effects. Table 11 presents the range of potential human health and ecological effects which can occur due to air toxics exposure. For several years, the primary focus of risk assessments and control programs designed to reduce air toxics has been cancer. Accord-

[51] Ranges reflect usage of alternate exposure-response functions.

Table 11. Health and Welfare Effects of Hazardous Air Pollutants.

Effect Category	Quantified Effects	Unquantified Effects	Other Possible Effects
Human Health	Cancer Mortality - nonutility stationary source - mobile source	Cancer Mortality - utility source - area source Noncancer effects - neurological - respiratory - reproductive - hematopoietic - developmental - immunological - organ toxicity	
Human Welfare		Decreased income and recreation opportunities due to fish advisories Odors	Decreased income resulting from decreased physical performance
Ecological		Effects on wildlife Effects on plants Ecosystem effects Loss of biological diversity	Effects on global climate
Other Welfare		Visibility Building Deterioration	Loss of biological diversity

ing to present EPA criteria, there are over 100 known or suspected carcinogens. EPA's 1990 Cancer Risk study indicated that as many as 1,000 to 3,000 cancers annually may be attributable to the air toxics for which assessments were available (virtually all of this estimate came from assessments of about a dozen well-studied pollutants).[52]

In addition to cancer, these pollutants can cause a wide variety of health effects, ranging from respiratory problems to reproductive and developmental effects. There has been considerably less work done to assess the magnitude of non-cancer effects from air toxics, but one survey study has shown that some pollutants are present in the atmosphere at reference levels that have caused adverse effects in animals.[53]

Emissions of air toxics can also cause adverse health effects via non-inhalation exposure routes. Persistent bioaccumulating pollutants, such as mercury and dioxins, can be deposited into water or soil and subsequently taken up by living organisms. The pollutants can biomagnify through the food chain and exist in high concentrations when consumed by humans in foods such as fish or beef. The resulting exposures can cause adverse effects in humans, and can also disrupt ecosystems by affecting top food chain species.

Finally, there are a host of other potential ecological and welfare effects associated with air toxics, for which very little exists in the way of quantitative analysis. Toxic effects of these pollutants have the potential to disrupt both terrestrial and aquatic ecosystems and contribute to adverse welfare effects such as fish consumption advisories in the Great Lakes.[54]

[52] U.S. EPA, Cancer Risk from Outdoor Exposure to Air Toxics. EPA-450/1-90-004f. Prepared by EPA/OAR/OAQPS.

[53] U.S. EPA, "Toxic Air Pollutants and Noncancer Risks: Screening Studies," External Review Draft, September, 1990.

[54] U.S. EPA, Office of Air Quality Planning and Standards. "Deposition of Air Pollutants to the Great Waters, First Report to Congress," May 1994. EPA-453/R-93-055.

Unfortunately, the effects of air toxics emissions reductions could not be quantified for the present study. Unlike criteria pollutants, there was relatively little monitoring data available for air toxics, and that which exists covered only a handful of pollutants. Emissions inventories were very limited and inconsistent, and air quality modeling has only been done for a few source categories. In addition, the scientific literature on the effects of air toxics was generally much weaker than that available for criteria pollutants.

Limitations in the underlying data and analyses of air toxics led the Project Team to exclude the available quantitative results from the primary analysis of CAA costs and benefits. The estimates of cancer incidence benefits of CAA air toxics control which were developed, but ultimately rejected, are presented in Appendix H. Also found in Appendix H is a list of research needs identified by the Project Team which, if met, would enable at least a partial assessment of air toxics benefits in future section 812 studies.

Uncertainty In The Physical Effects Estimates

As discussed above, and in greater detail in Appendix D, a number of important assumptions and uncertainties in the physical effects analysis may influence the estimate of monetary benefits presented in this study. Several of these key uncertainties, their potential directional bias, and the potential significance of this uncertainty for the overall results of the analysis are summarized in Table 12.

Table 12. Uncertainties Associated with Physical Effects Modeling.

Potential Source of Error	Direction of Potential Bias in Physical Effects Estimate	Significance Relative to Key Uncertainties in Overall Monetary Benefit Estimate
Estimation of $PM_{2.5}$ from modeled PM_{10} and TSP data (to support mortality estimation)	Unknown	Significant. Estimated $PM_{2.5}$ profiles are used to calculate most of the premature mortality. There is significant uncertainty about how the fine particle share of overall PM levels varies temporally and spatially throughout the 20 year period.
Extrapolation of health effects to populations distant from monitors (or monitored counties in the case of PM).	Probable overestimate.	Probably minor. In addition, this adjustment avoids the underestimation which would result by estimating effects for only those people living near monitors. Potential overestimate may result to the extent air quality in areas distant from monitors is significantly better than in monitored areas. This disparity should be quite minor for regional pollutants, such as ozone and fine particulates.
Estimation of degree of life-shortening associated with PM-related premature mortality.	Unknown.	Unknown, possibly significant when using a value of life-years approach. Varying the estimate of degree of prematurity has no effect on the aggregate benefit estimate when a value of statistical life approach is used since all incidences of premature mortality are valued equally. Under the alternative approach based on valuing individual life-years, the influence of alternative values for numbers of average life-years lost may be significant.
Assumption of zero lag between exposure and incidence of PM-related premature mortality.	Overestimate.	Probably minor. The short-term mortality studies indicate that a significant portion of the premature mortality associated with exposure to elevated PM concentrations is very short-term (i.e., a matter of a few days). In addition, the available epidemiological studies do not provide evidence of a significant lag between exposure and incidence. The lag is therefore likely to be a few years at most and application of reasonable discount rates over a few years would not alter the monetized benefit estimate significantly.
Choice of CR function (i.e., "across-study" uncertainties)	Unknown.	Significant. The differences in implied physical outcomes estimated by different underlying studies are large.
Uncertainty associated with CR functions derived from each individual study (i.e., "within study" uncertainty)	Unknown.	Probably minor.
Exclusion of potential UV-B attenuation benefits associated with higher concentrations of tropospheric ozone under the no-control case.	Overestimate.	Insignificant. In addition to the incomplete scientific evidence that there is a UV-B exposure disbenefit associated specifically with tropospheric ozone reductions, the potential contribution toward total ozone column attenuation from the tropospheric layer is probably very small.
Exclusion of potential substitution of ozone-resistant cultivars in agriculture analysis.	Overestimate.	Insignificant, given small relative contribution of quantified agricultural effects to overall quantified benefit estimate.
Exclusion of other agricultural effects (crops, pollutants)	Underestimate.	Unknown, possibly significant.
Exclusion of effects on terrestrial, wetland, and aquatic ecosystems, and forests.	Underestimate.	Unknown, possibly significant.
No quantification of materials damage	Underestimate	Unknown, possibly significant.

6

Economic Valuation

Estimating the reduced incidence of physical effects represents a valuable measure of health benefits for individual endpoints; however, to compare or aggregate benefits across endpoints, the benefits must be monetized. Assigning a monetary value to avoided incidences of each effect permits a summation, in terms of dollars, of monetized benefits realized as a result of the CAA, and allows that summation to be compared to the cost of the CAA.

For the present analysis of health and welfare benefits, valuation estimates were obtained from the economic literature, and are reported in dollars per case reduced for health effects and dollars per unit of avoided damage for welfare effects.[55] Similar to estimates of physical effects provided by health studies, each of the monetary values of benefits applied in this analysis is reported in terms of a mean value and a probability distribution around the mean estimate. The statistical form of the probability distribution used for the valuation measures varies by endpoint. For example, while the estimate of the dollar value of an avoided premature mortality is described by the Weibull distribution, the estimate for the value of a reduced case of acute bronchitis is assumed to be uniformly distributed between a minimum and maximum value.

Methods for Valuation of Health and Welfare Effects

In environmental benefit-cost analysis, the dollar value of an environmental benefit (e.g., a health-related improvement in environmental quality) conferred on a person is the dollar amount such that the person would be indifferent between having the environmental benefit and having the money. In some cases, this value is measured by studies which estimate the dollar amount required to compensate a person for new or additional exposure to an adverse effect. Estimates derived in this manner are referred to as “willingness-to-accept” (WTA) estimates. In other cases, the value of a welfare change is measured by estimating the amount of money a person is willing to pay to eliminate or reduce a current hazard. This welfare change concept is referred to as “willingness-to-pay” (WTP). For small changes in risk, WTP and WTA are virtually identical, primarily because the budget constraints normally associated with expressions of WTP are not significant enough to drive a wedge between the estimates. For larger risk changes, however, the WTP and WTA values may diverge, with WTP normally being less than WTA because of the budget constraint effect. While the underlying economic valuation literature is based on studies which elicited expressions of WTP and/or WTA, the remainder of this report refers to all valuation coefficients as WTP estimates. In some cases (e.g., stroke-related hospital admissions), neither WTA nor WTP estimates are available and WTP is approximated by cost of illness (COI) estimates, a clear underestimate of the true welfare change since important value components (e.g., pain and suffering associated with the stroke) are not reflected in the out-of-pocket costs for the hospital stay.

For most goods, WTP can be observed by examining actual market transactions. For example, if a gallon of bottled drinking water sells for one dollar, it can be observed that at least some persons are willing to pay one dollar for such water. For goods that are not exchanged in the market, such as most environmental “goods,” valuation is not so straightforward. Nevertheless, value may be inferred from observed behavior, such as through estimation of the WTP for mortality risk reductions based on observed sales and prices of safety devices such as smoke detectors. Alternatively, surveys may be used in an attempt to elicit directly WTP for an environmental improvement.

Wherever possible, this analysis uses estimates of the mean WTP of the U.S. population to avoid an environmental effect as the value of avoiding that effect. In some cases, such estimates are not available, and the cost of mitigating or avoiding the effect is used as a rough estimate of the value of avoiding the effect. For example, if an effect results in hospitalization, the avoided medical costs were considered as a possible estimate of the value of avoiding the effect. Finally, where even the “avoided cost” estimate is not available, the analysis relies on other available methods to provide a rough approximation of WTP. As noted above, this analysis uses a range of values for most environmental effects, or endpoints. Table 13

[55] The literature reviews and valuation estimate development process is described in detail in Appendix I and in the referenced supporting reports.

Table 13. Health and Welfare Effects Unit Valuation (1990 dollars).

Endpoint	Pollutant	Valuation (mean est.)	
Mortality	PM & Pb	$4,800,000	per case
Chronic Bronchitis	PM	$260,000	per case
IQ Changes			
Lost IQ Points	Pb	$3,000	per IQ point
IQ < 70	Pb	$42,000	per case
Hypertension	Pb	$680	per case
Strokes*	Pb	$200,000 $150,000	per case-males per case-females
Coronary Heart Disease	Pb	$52,000	per case
Hospital Admissions			
Ischemic Heart Disease	PM	$10,300	per case
Congestive Heart Failure	PM	$8,300	per case
COPD	PM & O_3	$8,100	per case
Pneumonia	PM & O3	$7,900	per case
All Respiratory	PM & O_3	$6,100	per case
Respiratory Illness and Symptoms			
Acute Bronchitis	PM	$45	per case
Acute Asthma	PM & O_3	$32	per case
Acute Respiratory Symptoms	PM, O_3, NO_2, SO_2	$18	per case
Upper Respiratory Symptoms	PM	$19	per case
Lower Respiratory Symptoms	PM	$12	per case
Shortness of Breath	PM	$5.30	per day
Work Loss Days	PM	$83	per day
Mild Restricted Activity Days	PM & O_3	$38	per day
Welfare Benefits			
Visibility	DeciView	$14	per unit change in DeciView
Household Soiling	PM	$2.50	per household per PM_{10} change
Decreased Worker Productivity	O_3	$1	**
Agriculture (Net Surplus)	O_3	Estimated Change In Economic Surplus	

* Strokes are comprised of atherothrombotic brain infarctions and cerebrovascular accidents; both are estimated to have the same monetary value.
** Decreased productivity valued as change in daily wages: $1 per worker per 10% decrease in O_3.

provides a summary of the mean unit value estimates used in the analysis. The full range of values can be found in Appendix I.

Mortality

Some forms of air pollution increase the probability that individuals will die prematurely. The concentration-response functions for mortality used in this analysis express this increase in mortality risk as cases of "excess premature mortality" per time period (e.g., per year).

The benefit, however, is the avoidance of small increases in the risk of mortality. If individuals' WTP to avoid small increases in risk is summed over enough individuals, the value of a statistical premature death avoided can be inferred.[56] For expository purposes, this valuation is expressed as "dollars per mortality avoided," or "value of a statistical life" (VSL), even though the actual valuation is of small changes in mortality risk.

The mortality risk valuation estimate used in this study is based on an analysis of 26 policy-relevant value-of-life studies (see Table 14). Five of the 26 studies are contingent valuation (CV) studies, which directly solicit WTP information from subjects; the rest are wage-risk studies, which base WTP estimates on estimates of the additional compensation demanded in the labor market for riskier jobs. The Project Team used the best estimate from each of the 26 studies to construct a distribution of mortality risk valuation estimates for the section 812 study. A Weibull distribution, with a mean of $4.8 million and standard deviation of $3.24 million, provided the best fit to the 26 estimates. There is considerable uncertainty associated with this approach, however, which is discussed in detail later in this chapter and in Appendix I.

In addition, the Project Team developed alternative calculations based on a life-years lost approach. To employ the value of statistical life-year (VSLY) approach, the Project Team had to first estimate the age distribution of those lives which would be saved by reducing air pollution. Based on life expectancy tables, the life-years saved from each statistical life saved within each age and sex cohort were calculated. To value these statistical life-years, a conceptual model was hypothesized which depicted the relationship between the value of life and the value of life-years. As noted earlier in Table 9, the average number of life-years saved across all age groups for which data were available are 14 for PM-related mortality and 38 for Pb-related mortality. The

[56] Because people are valuing small decreases in the risk of premature mortality, it is expected deaths that are inferred. For example, suppose that a given reduction in pollution confers on each exposed individual a decrease in mortal risk of 1/100,000. Then among 100,000 such individuals, one fewer individual can be expected to die prematurely . If each individual's WTP for that risk reduction is $50, then the implied value of a statistical premature death avoided is $50 x 100,000 = $5 million.

Table 14. Summary of Mortality Valuation Estimates (millions of $1990)

Study	Type of Estimate	Valuation (millions 1990$)
Kneisner and Leeth (1991) (US)	Labor Market	0.6
Smith and Gilbert (1984)	Labor Market	0.7
Dillingham (1985)	Labor Market	0.9
Butler (1983)	Labor Market	1.1
Miller and Guria (1991)	Cont. Value	1.2
Moore and Viscusi (1988a)	Labor Market	2.5
Viscusi, Magat, and Huber (1991b)	Cont. Value	2.7
Gegax et al. (1985)	Cont. Value	3.3
Marin and Psacharopoulos (1982)	Labor Market	2.8
Kneisner and Leeth (1991) (Australia)	Labor Market	3.3
Gerking, de Haan, and Schulze (1988)	Cont. Value	3.4
Cousineau, Lacroix, and Girard (1988)	Labor Market	3.6
Jones-Lee (1989)	Cont. Value	3.8
Dillingham (1985)	Labor Market	3.9
Viscusi (1978, 1979)	Labor Market	4.1
R.S. Smith (1976)	Labor Market	4.6
V.K. Smith (1976)	Labor Market	4.7
Olson (1981)	Labor Market	5.2
Viscusi (1981)	Labor Market	6.5
R.S. Smith (1974)	Labor Market	7.2
Moore and Viscusi (1988a)	Labor Market	7.3
Kneisner and Leeth (1991) (Japan)	Labor Market	7.6
Herzog and Schlottman (1987)	Labor Market	9.1
Leigh and Folson (1984)	Labor Market	9.7
Leigh (1987)	Labor Market	10.4
Gaten (1988)	Labor Market	13.5
SOURCE: Viscusi, 1992		

average for PM, in particular, differs from the 35-year expected remaining lifespan derived from existing wage-risk studies.[57]

Using the same distribution of value of life estimates used above (i.e. the Weibull distribution with a mean estimate of $4.8 million), a distribution for the value of a life-year was then estimated and combined with the total number of estimated life-years lost. The details of these calculations are presented in Appendix I.

Survey-Based Values

Willingness-to pay for environmental improvement is often elicited through survey methods (such as the "contingent valuation" method). Use of such methods in this context is controversial within the economics profession. In general, economists prefer to infer WTP from observed behavior. There are times when such inferences are impossible, however, and some type of survey technique may be the only means of eliciting WTP. Economists' beliefs regarding the reliability of such survey-based data cover a broad spectrum, from unqualified acceptances of the results of properly-conducted surveys to outright rejections of all survey-based valuations.

In this analysis, unit valuations which rely exclusively on the contingent valuation method are chronic bronchitis, respiratory-related ailments, minor restricted activity days, and visibility. As indicated above, the value derived for excess premature mortality stems from 26 studies, of which five use the contingent valuation method. These five studies are within the range of the remaining 21 labor market studies. All five report mortality valuations lower than the central estimate used in this analysis. Excluding the contingent valuation studies from the mortality valuation estimate would yield a central estimate approximately ten percent higher than the 4.8 million dollar value reported above. The endpoints with unit valuations based exclusively on contingent valuation account for approximately 30 percent of the present value of total monetized benefits. Most of the CV-based benefits are attributable to avoided cases of chronic bronchitis.

Chronic Bronchitis

The best available estimate of WTP to avoid a case of chronic bronchitis (CB) comes from Viscusi et al.(1991). The case of CB described to the respondents in the Viscusi study, however, was described by the authors as a severe case. The Project Team employed an estimate of WTP to avoid a pollution-related case of CB that was based on adjusting the WTP to avoid a severe case, estimated by Viscusi et al. (1991), to account for the likelihood that an average case of pollution-related CB is not as severe as the case described in the Viscusi study.

The central tendency estimate of WTP to avoid a pollution-related case of chronic bronchitis (CB) used in this analysis is the mean of a distribution of WTP estimates. This distribution incorporates the uncertainty from three sources: (1) the WTP to avoid a case of severe CB, as described by Viscusi et al., 1991; (2) the severity level of an average pollution-related case

[57] See, for example, Moore and Viscusi (1988) or Viscusi (1992).

of CB (relative to that of the case described by Viscusi et al.(1991); and (3) the elasticity of WTP with respect to severity of the illness. Based on assumptions about the distributions of each of these three uncertain components, a distribution of WTP to avoid a pollution-related case of CB was derived by Monte Carlo methods. The mean of this distribution, which was about $260,000, is taken as the central tendency estimate of WTP to avoid a pollution-related case of CB. The three underlying distributions, and the generation of the resulting distribution of WTP, are described in Appendix I.

Respiratory-Related Ailments

In general, the valuations assigned to the respiratory-related ailments listed in Table 14 represent a combination of willingness to pay estimates for individual symptoms which comprise each ailment. For example, a willingness to pay estimate to avoid the combination of specific upper respiratory symptoms defined in the concentration-response relationship measured by Pope et al. (1991) is not available. However, while that study defined upper respiratory symptoms as one suite of ailments (runny or stuffy nose; wet cough; and burning, aching, or red eyes), the valuation literature reported individual WTP estimates for three closely matching symptoms (head/sinus congestion, cough, and eye irritation). The available WTP estimates were therefore used as a surrogate to the values for the precise symptoms defined in the concentration-response study.

To capture the uncertainty associated with the valuation of respiratory-related ailments, this analysis incorporated a range of values reflecting the fact that an ailment, as defined in the concentration-response relationship, could be comprised of just one symptom or several. At the high end of the range, the valuation represents an aggregate of WTP estimates for several individual symptoms. The low end represents the value of avoiding a single mild symptom.

Minor Restricted Activity Days

An individual suffering from a single severe or a combination of pollution-related symptoms may experience a Minor Restricted Activity Day (MRAD). Krupnick and Kopp (1988) argue that mild symptoms will not be sufficient to result in a MRAD, so that WTP to avoid a MRAD should exceed WTP to avoid any single mild symptom. On the other hand, WTP to avoid a MRAD should not exceed the WTP to avoid a work loss day (which results when the individual experiences more severe symptoms). No studies are reported to have estimated WTP to avoid a day of minor restricted activity. Instead, this analysis uses an estimate derived from WTP estimates for avoiding combinations of symptoms which may result in a day of minor restricted activity ($38 per day). The uncertainty range associated with this value extends from the highest value for a single symptom to the value for a work loss day. Furthermore, the distribution acknowledges that the actual value is likely to be closer to the central estimate than either extreme.

Visibility

The value of avoided visibility impairment was derived from existing contingent valuation studies of the household WTP to improve visibility, as reported in the economics literature. These studies were used to define a single, consistent basis for the valuation of visibility benefits nationwide. The central tendency of the benefits estimate is based on an annual WTP of $14 per household per unit improvement in the DeciView index, with upper and lower bounds of $21 and $8, respectively, on the uncertainty range of the estimate.

Avoided Cost Estimates

For some health effects, WTP estimates are not available, and the Project Team instead used “costs avoided” as a substitute for WTP. Avoided costs were used to value the following endpoints: hypertension, hospital admissions, and household soiling.

Hypertension and Hospital Admissions

Avoided medical costs and the avoided cost of lost work time were used to value hypertension (high blood pressure) and hospital admissions (this includes hospital admissions for respiratory ailments as well as heart disease, heart attacks, and strokes) .

For those hospital admissions which were specified to be the initial hospital admission (in particular, hospital admissions for coronary heart disease (CHD) events and stroke), avoided cost estimates should consist of the present discounted value of the stream of medical expenditures related to the illness, as well as the present discounted value of the stream of lost earnings related to the illness. While an estimate of present discounted value of both medical expenditures and lost earnings was available for stroke ($200,000 for males and $150,000 for females), the best available estimate for CHD ($52,000) did not include lost earnings. Although no published estimates of the value of lost earnings due to CHD events are available, one unpublished study suggests that this value could be substantial, possibly exceeding the value of medical expenditures. The estimate of $52,000 for CHD may therefore be a substantial underestimate. The derivations of the avoided cost estimates for CHD and stroke are discussed in Appendix G.

In those cases for which it is unspecified whether the hospital admission is the initial one or not (that is, for all hospital admissions endpoints other than CHD and stroke), it is unclear what portion of medical expenditures and lost earnings after hospital discharge can reasonably be attributed to pollution exposure and what portion might have resulted from an individual's pre-existing condition even in the absence of a particular pollution-related hospital admission. In such cases, the estimates of avoided cost include only those costs associated with the hospital stay, including the hospital charge, the associated physician charge, and the lost earnings while in the hospital ($6,100 to $10,300, depending on the ailment for which hospitalization is required).

The estimate of avoided cost for hypertension included physician charges, medication costs, and hospitalization costs, as well as the cost of lost work time, valued at the rate estimated for a work loss day (see discussion below). Based on this approach, the value per year of avoiding a case of hypertension is taken to equal the sum of medical costs per year plus work loss costs per year; the resulting value is $680 per case per year.

Presumably, willingness-to-pay to avoid the effects (and treatment) of hypertension would reflect the value of avoiding any associated pain and suffering, and the value placed on dietary changes, etc. Likewise, the value of avoiding a health effect that would require hospitalization or doctor's care would include the value of avoiding the pain and suffering caused by the health effect as well as lost leisure time, in addition to medical costs and lost work time. Consequently, the valuations for these endpoints used in this analysis likely represent lower-bound estimates of the true social values for avoiding such health effects.

Household Soiling

This analysis values benefits for this welfare effect by considering the avoided costs of cleaning houses due to particulate matter soiling. The Project Team's estimate reflects the average household's annual cost of cleaning per $\mu g/m^3$ particulate matter ($2.50). Considered in this valuation are issues such as the nature of the particulate matter, and the proportion of households likely to do the cleaning themselves. Since the avoided costs of cleaning used herein do not reflect the loss of leisure time (and perhaps work time) incurred by those who do their own cleaning, the valuation function likely underestimates true WTP to avoid additional soiling.

Other Valuation Estimates

Changes in Children's IQ

One of the major effects of lead exposure is permanently impaired cognitive development in children. No ready estimates of society's WTP for improved cognitive ability are currently available. Two effects of IQ decrements can be monetized, however: reductions in expected lifetime income, and increases in societal expenditures for compensatory education. These two effects almost certainly understate the WTP to avoid impaired cognitive development in children, and probably should be considered lower bound estimates. In the absence of better estimates, however, the Project Team has assumed that the two monetized effects represent a useful approximation of WTP.

The effect of IQ on expected lifetime income comprises a direct and an indirect effect. The direct effect is drawn from studies that estimate, all else being equal, the effect of IQ on income. The indirect effect occurs as a result of the influence of IQ on educational attainment: higher IQ leads to more years of education, and more education leads in turn to higher expected future income. However, this indirect benefit is mitigated, but not eliminated, by the added costs of the additional education and by the potential earnings forgone by the student while enrolled in school.[58] Combining the direct and indirect influences, the net effect of higher IQ on expected lifetime income (dis-

[58] Theoretically, the indirect effect should be small relative to the direct effect of IQ on future earnings. The empirical research used to derive values for this analysis, however, implies that the indirect effect is roughly equal in magnitude to the direct effect. One can infer from this information that there is a market distortion of some sort present (such as imperfect knowledge of the returns to education), or, perhaps, that individuals make their education "investments" for purposes other than (or in addition to) "maximizing lifetime income." See Appendix G for further discussion of this issue.

counted to the present at five percent) is estimated to be $3,000 per additional IQ point.

In this analysis, it is assumed that part-time compensatory education is required for all children with IQ less than 70. The Project Team assumed that the WTP to avoid cases of children with IQ less than 70 can be approximated by the cost ($42,000 per child) of part-time special education in regular classrooms from grades one through twelve (as opposed to independent special education programs), discounted to the present at five percent. See Appendix G for more detail on valuation methods and data sources for IQ effects and other lead-related health impacts.

Work Loss Days and Worker Productivity

For this analysis, it was assumed that the median daily 1990 wage income of 83 dollars was a reasonable approximation of WTP to avoid a day of lost work. Although a work loss day may or may not affect the income of the worker, depending on the terms of employment, it does affect economic output and is thus a cost to society. Conversely, avoiding the work loss day is a benefit.

A decline in worker productivity has been measured in outdoor workers exposed to ozone. Reduced productivity is measured in terms of the reduction in daily income of the average worker engaged in strenuous outdoor labor, estimated at $1 per 10 percent increase in ozone concentration.

Agricultural Benefits

Similar to the other welfare effects, the agricultural benefits analysis estimated benefits in dollars per unit of avoided damage, based on estimated changes in crop yields predicted by an agricultural sector model. This model incorporated agricultural price, farm policy, and other data for each year. Based on expected yields, the model estimated the production levels for each crop, and the economic benefits to consumers, and to producers, associated with these production levels. To the extent that alternative exposure-response relationships were available, a range of potential benefits was calculated (see Appendix F).

Valuation Uncertainties

The Project Team attempted to handle most valuation uncertainties explicitly and quantitatively by expressing values as distributions (see Appendix I for a complete description of distributions employed), using a Monte-Carlo simulation technique to apply the valuations to physical effects (see Chapter 7) with the mean of each valuation distribution equal to the "best estimate" valuation. This approach does not, of course, guarantee that all uncertainties have been adequately characterized, nor that the valuation estimates are unbiased. It is possible that the actual WTP to avoid an air pollution-related impact is outside of the range of estimates used in this analysis. Nevertheless, the Project Team believes that the distributions employed are reasonable approximations of the ranges of uncertainty, and that there is no compelling reason to believe that the mean values employed are systematically biased (except for the IQ-related and avoided cost-based values, both of which probably underestimate WTP).

One particularly important area of uncertainty is valuation of mortality risk reduction. As noted in Chapter 7, changes in mortality risk are a very important component of aggregate benefits, and mortality risk valuation is an extremely large component of the quantified uncertainty. Consequently, any uncertainty concerning mortality risk valuation beyond that addressed by the quantitative uncertainty assessment (i.e., that related to the Weibull distribution with a mean value of $4.8 million) deserves note. One issue merits special attention: uncertainties and possible biases related to the "benefits transfer" from the 26 valuation source studies to valuation of reductions in PM-related mortality rates.

Mortality Risk Benefits Transfer

Although each of the mortality risk valuation source studies (see Table 14) estimated the average WTP for a given reduction in mortality risk, the degree of reduction in risk being valued varied across studies and is not necessarily the same as the degree of mortality risk reduction estimated in this analysis. The transferability of estimates of the value of a statistical life from the 26 studies to the section 812 benefit analysis rests on the assumption that, within a reasonable range, WTP for reductions in mortality risk is linear in risk reduction. For example, suppose a study estimates that the average WTP for a reduction in mortality risk of 1/100,000 is 50 dollars, but that the actual mortality risk reduction resulting from a given pollutant reduction is 1/10,000. If WTP for reductions in mortality risk is linear in risk reduction, then a WTP of 50 dollars for a reduction of 1/100,000 implies a WTP of 500 dollars for a risk reduction of 1/10,000 (which is ten times the risk reduction valued in the study). Under the assumption of linearity, the estimate of the value of a statistical life does not depend on the particular amount of risk reduction being valued.

Although the particular amount of mortality risk reduction being valued in a study may not affect the transferability of the WTP estimate from the study to the benefit analysis, the characteristics of the study subjects and the nature of the mortality risk being valued in the study could be important. Certain characteristics of both the population affected and the mortality risk facing that population are believed to affect the average WTP to reduce risk. The appropriateness of the mean of the WTP estimates from the 26 studies for valuing the mortality-related benefits of reductions in pollutant concentrations therefore depends not only on the quality of the studies (i.e., how well they measure what they are trying to measure), but also on (1) the extent to which the subjects in the studies are similar to the population affected by changes in air pollution and (2) the extent to which the risks being valued are similar.

The substantial majority of the 26 studies relied upon are wage-risk (or labor market) studies. Compared with the subjects in these wage-risk studies, the population most affected by air pollution-related mortality risk changes is likely to be, on average, older and probably more risk averse. Some evidence suggests that approximately 85 percent of those identified in short-term ("episodic") studies who die prematurely from PM-related causes are over 65.[59] The average age of subjects in wage-risk studies, in contrast, would be well under 65.

The direction of bias resulting from the age difference is unclear. It could be argued that, because an older person has fewer expected years left to lose, his or her WTP to reduce mortality risk would be less than that of a younger person. This hypothesis is supported by one empirical study, Jones-Lee et al. (1985), which found WTP to avoid mortality risk at age 65 to be about 90 percent of what it is at age 40. On the other hand, there is reason to believe that those over 65 are, in general, more risk averse than the general population, while workers in wage-risk studies are likely to be less risk averse than the general population. Although the list of 26 studies used here excludes studies that consider only much-higher-than-average occupational risks, there is nevertheless likely to be some selection bias in the remaining studies—that is, these studies are likely to be based on samples of workers who are, on average, more risk-loving than the general population. In contrast, older people as a group exhibit more risk-averse behavior.

There is substantial evidence that the income elasticity of WTP for health risk reductions is positive (although there is uncertainty about the exact value of this elasticity). Individuals with higher incomes (or greater wealth) should, then, be willing to pay more to reduce risk, all else equal, than individuals with lower incomes or wealth. The comparison between the (actual and potential) income or wealth of the workers in the wage-risk studies versus that of the population of individuals most likely to be affected by changes in pollution concentrations, however, is unclear. One could argue that because the elderly are relatively wealthy, the affected population is also wealthier, on average, than are the wage-risk study subjects, who tend to be middle-aged (on average) blue-collar workers. On the other hand, the workers in the wage-risk studies will have potentially more years remaining in which to acquire streams of income from future earnings. In addition, it is possible that among the elderly it is largely the poor elderly who are most vulnerable to air pollution-related mortality risk (e.g., because of generally poorer health care). On net, the potential income comparison is unclear.

Although there may be several ways in which job-related mortality risks differ from air pollution-related mortality risks, the most important difference may be that job-related risks are incurred voluntarily whereas air pollution-related risks are incurred involuntarily. There is some evidence[60] that people will pay more to reduce involuntarily incurred risks than risks incurred voluntarily. If this is the case, WTP estimates based on wage-risk studies may be downward biased estimates of WTP to reduce involuntarily incurred air pollution-related mortality risks.

[59] See Schwartz and Dockery (1992), Ostro et al. (1995), and Chestnut (1995).

[60] See, for example, Violette and Chestnut, 1983.

Finally, another important difference related to the nature of the risk may be that some workplace mortality risks tend to involve sudden, catastrophic events, whereas air pollution-related risks tend to involve longer periods of disease and suffering prior to death. Some evidence suggests that WTP to avoid a risk of a protracted death involving prolonged suffering and loss of dignity and personal control is greater than the WTP to avoid a risk (of identical magnitude) of sudden death. To the extent that the mortality risks addressed in this assessment are associated with longer periods of illness or greater pain and suffering than are the risks addressed in the valuation literature, the WTP measurements employed in the present analysis would reflect a downward bias.

The potential sources of bias introduced by relying on wage-risk studies to derive an estimate of the WTP to reduce air pollution-related mortality risk are summarized in Table 15. Among these potential biases, it is disparities in age and income between the subjects of the wage-risk studies and those affected by air pollution which have thus far motivated specific suggestions for quantitative adjustment[61]; however, the appropriateness and the proper magnitude of such potential adjustments remain unclear given presently available information. These uncertainties are particularly acute given the possibility that age and income biases might offset each other in the case of pollution-related mortality risk aversion. Furthermore, the other potential biases discussed above, and summarized in Table 16, add additional uncertainty regarding the transferability of WTP estimates from wage-risk studies to environmental policy and program assessments.

Table 15. Estimating Mortality Risk Based on Wage-Risk Studies: Potential Sources and Likely Direction of Bias.

Factor	Likely Direction of Bias in WTP Estimate
Age	Uncertain, perhaps upward
Degree of Risk Aversion	Downward
Income	Uncertain
Voluntary vs. Involuntary	Downward
Catastrophic vs. Protracted Death	Uncertain, perhaps downward

[61] Chestnut, 1995; IEc, 1992.

7

Results and Uncertainty

This chapter presents a summary of the monetized benefits of the CAA from 1970 to 1990, compares these with the corresponding costs, explores some of the major sources of uncertainty in the benefits estimates, and presents alternative results reflecting diverging viewpoints on two key variables: PM-related mortality valuation and the discount rate.

Monetized economic benefits for the 1970 to 1990 period were derived by applying the unit valuations discussed in Chapter 6 to the stream of physical effects estimated by the method documented in Chapter 5. The range of estimates for monetized benefits is based on the quantified uncertainty associated with the health and welfare effects estimates and the quantified uncertainty associated with the unit valuations applied to them. Quantitative estimates of uncertainties in earlier steps of the analysis (i.e., estimation of compliance costs,[62] emissions changes, and air quality changes) could not be adequately developed and are therefore not applied in the present study. As a result, the range of estimates for monetized benefits presented in this chapter is narrower than would be expected with a complete accounting of the uncertainties in all analytical components. However, the uncertainties in the estimates of physical effects and unit values are considered to be large relative to these earlier components. The characterization of the uncertainty surrounding unit valuations is discussed in detail in Appendix I. The characterization of the uncertainty surrounding health and welfare effects estimates, as well as the characterization of overall uncertainty surrounding monetized benefits, is discussed below.

Quantified Uncertainty in the Benefits Analysis

Alternative studies published in the scientific literature which examine the health or welfare consequences of exposure to a given pollutant often obtain different estimates of the concentration-response (CR) relationship between the pollutant and the effect. In some instances the differences among CR functions estimated by, or derived from, the various studies are substantial. In addition to sampling error, these differences may reflect actual variability of the concentration-response relationship across locations. Instead of a single CR coefficient characterizing the relationship between an endpoint and a pollutant in the CR function, there could be a distribution of CR coefficients which reflect geographic differences.[63] Because it is not feasible to estimate the CR coefficient for a given endpoint-pollutant combination in each county in the nation, however, the national benefits analysis applies the mean of the distribution of CR coefficients to each county. This mean is estimated based on the estimates of CR coefficients reported in the available studies and the information about the uncertainty of these estimates, also reported in the studies.

Based on the assumption that for each endpoint-pollutant combination there is a distribution of CR coefficients, the Project team used a Monte Carlo approach to estimate the mean of each distribution and to characterize the uncertainty surrounding each estimate. For most health and welfare effects, only a single study is considered. In this case, the best estimate of the mean of the distribution of CR coefficients is the reported estimate in the study. The uncertainty surrounding the estimate of the mean CR coefficient is

[62] Although compliance cost estimation is primarily of concern to the cost side of this analysis, uncertainty in the estimates for compliance costs does influence the uncertainty in the benefit estimates because compliance cost changes were used to estimate changes in macroeconomic conditions which, in turn, influenced the estimated changes in emissions, air quality, and physical effects.

[63] Geographic variability may result from differences in lifestyle (e.g., time spent indoors vs outdoors), deposition rates, or other localized factors which influence exposure of the population to a given atmospheric concentration of the pollutant.

best characterized by the standard error of the reported estimate. This yields a normal distribution, centered at the reported estimate of the mean. If two or more studies are considered for a given endpoint-pollutant combination, a normal distribution is derived for each study, centered at the mean estimate reported in the study. On each iteration of a Monte Carlo procedure, a CR coefficient is randomly selected from each of the normal distributions, and the selected values are averaged. This yields an estimate of the mean CR coefficient for that endpoint-pollutant combination. Iterating this procedure many times results in a distribution of estimates of the mean CR coefficient.

Each estimate randomly selected from this distribution was evaluated for each county in the nation, and the results were aggregated into an estimate of the national incidence of the health or welfare effect. Through repeated sampling from the distribution of mean CR coefficients, a distribution of the estimated change in effect outcomes due to the change in air quality between the control and no-control scenarios was generated.

Once a distribution of estimated outcomes was generated for each health and welfare effect, Monte Carlo methods were used again to characterize the overall uncertainty surrounding monetized benefits. For each health and welfare effect in a set of non-overlapping effects, an estimated incidence was randomly selected from the distribution of estimated incidences for that endpoint, and a unit value was randomly selected from the corresponding distribution of unit values, on each iteration of the Monte Carlo procedure. The estimated monetized benefit for that endpoint produced on that iteration is the product of these two factors. Repeating the process many times generated a distribution of estimated monetized benefits by endpoint. Combining the results for the individual endpoints using the Monte Carlo procedure yielded a distribution of total estimated monetized benefits for each target year (1975, 1980, 1985 and 1990). This technique enabled a representation of uncertainty in current scientific and economic opinion in these benefits estimates.

Aggregate Monetized Benefits

For each of the target years of the analysis, the monetized benefits associated with the different health and welfare effects for that year must be aggregated. These aggregate benefits by target year must then be aggregated across the entire 1970 to 1990 period of the study to yield a present discounted value of aggregate benefits for the period. The issues involved in each stage of aggregation, as well as the results of aggregation, are presented in this section. (The detailed results for the target years are presented in Appendix I.)

Table 16. Present Value of 1970 to 1990 Monetized Benefits by Endpoint Category for 48 State Population (billions of $1990, discounted to 1990 at 5 percent).

		Present Value		
Endpoint	**Pollutant(s)**	**5th %ile**	**Mean**	**95th %ile**
Mortality	PM	$2,369	$16,632	$40,597
Mortality	Pb	$121	$1,339	$3,910
Chronic Bronchitis	PM	$409	$3,313	$10,401
IQ (Lost IQ Pts. + Children w/ IQ<70)	Pb	$271	$399	$551
Hypertension	Pb	$77	$98	$120
Hospital Admissions	PM, O3, Pb, & CO	$27	$57	$120
Respiratory-Related Symptoms, Restricted Activity, & Decreased Productivity	PM, O3, NO2, & SO2	$123	$182	$261
Soiling Damage	PM	$6	$74	$192
Visibility	particulates	$38	$54	$71
Agriculture (Net Surplus)	O3	$11	$23	$35

Table 16 presents monetized benefits for each quantified and monetized health and welfare endpoint (or group of endpoints), aggregated from 1970 to 1990. The mean estimate resulting from the Monte Carlo simulation is presented, along with the measured credible range (upper and lower fifth percentiles of the distribution). Aggregating the stream of monetized benefits across years involved compounding the stream of monetized benefits estimated for each year to the 1990 present value (using a five percent discount rate).

Since the present value estimates combine streams of benefits from 1970 to 1990, the calculation required monetized estimates for each year. However, Monte Carlo modeling was carried out only for the four target years (1975, 1980, 1985 and 1990). In the intervening years, only a central estimate of benefits was estimated for each health and welfare endpoint (by multiplying the central incidence estimate for the given year by the central estimate of the unit valuation). The resulting annual benefit estimates provided a temporal trend of monetized benefits across the period resulting from the annual changes in air quality. They did not, however, characterize the uncertainty associated with the yearly estimates for intervening years. In an attempt to capture uncertainty associated with these estimates, the Project Team relied on the ratios of the 5th percentile to the mean and the 95th percentile to the mean in the target years. In general, these ratios were fairly constant across the target years, for a given endpoint. The ratios were interpolated between the target years, yielding ratios for the intervening years. Multiplying the ratios for each intervening year by the central estimate generated for that year provided estimates of the 5th and 95th percentiles, which were used to characterize uncertainty about the central estimate. Thus, the present value of the stream of benefits, including the credible range estimates, could be computed.

Table 16 offers a comparison of benefits by health or welfare endpoint. The effect categories listed in the table are mutually exclusive, allowing the monetized benefits associated with them to be added. It should be noted, however, that the listed categories combine estimates that are not mutually exclusive. To avoid double counting, care was taken to treat the benefits associated with overlapping effects as alternative estimates. For example, the “Hospital Admissions” category includes admissions for specific ailments (Pneumonia and COPD) as well as the broader classification of “all respiratory” ailments. Clearly, benefits accruing from the first two represent a subset of the last and adding all three together would result in an overestimate of total monetized benefits. To avoid this, the sum of benefits from Pneumonia and COPD was treated as an alternative to the benefits estimated for all respiratory ailments (the sum of the first two was averaged with the third). This issue of double-counting also arose for two other cases of overlapping health effects, both of which have been combined into the “Respiratory-Related Symptoms, Restricted Activity, & Decreased Productivity” category in Table 16. First, acute bronchitis was treated as an alternative (i.e., averaged with) the combination of upper and lower respiratory symptoms, since their definitions of symptoms overlap. Second, various estimates of restricted activity, with different degrees of severity, were combined into a single benefit category.

Table 17 reports the estimated total national monetized benefits attributed in this analysis to the CAA from 1970 to 1990. The benefits, valued in 1990 dollars, range from \$5.6 to \$49.4 trillion with a central estimate of \$22.2 trillion. The Monte Carlo technique was used to aggregate monetized benefits across endpoints. For each of several thousand iterations, a random draw of the monetized benefits for each endpoint was selected from the distributions summarized in

Table 17. Total Monetized Benefits for 48 State Population (Present Value in billions of 1990\$, discounted to 1990 at 5 percent).

	Present Value		
	5th %ile	Mean	95th %ile
TOTAL (Billions of 1990-value dollars)	\$5,600	\$22,200	\$49,400

Table 16 and the individual endpoint estimates were then summed. This resulted in the distribution of total national monetized benefits reported above.[64]

The temporal pattern of benefits during the 1970 to 1990 period is related to the difference in emissions between the control and no-control scenarios and is magnified by population growth during that period. As illustrated by Figure 18, quantified annual benefits increased steadily during the study period, with the greatest increases occurring during the late 1970s. The mean estimate of quantified annual benefits grew from 355 billion dollars in 1975 (expressed as inflation-adjusted 1990 dollars) to 930 billion dollars in 1980, 1,155 billion dollars in 1985, and 1,248 billion dollars in 1990.

Figure 19 depicts the distribution of monetized benefits for 1990 (similar distributions were generated for other years in the analysis period). The solid vertical bars in the figure represent the relative frequency of a given result in the 1990 Monte Carlo analysis. The largest bar, located above the "<$1,000", indicates that more Monte Carlo iterations generated monetized benefits of $900 billion to $1 trillion than in any other $100 billion range bin, making this the modal bin. The expected value of the estimate for total monetized benefit for 1990 (i.e., the mean of the distribution) is $1.25 trillion. The ninety percent confidence interval, a summary description of the spread of a distribution, is also noted in the figure.

Figure 18. Monte Carlo Simulation Model Results for Target Years (in billions of 1990 dollars).

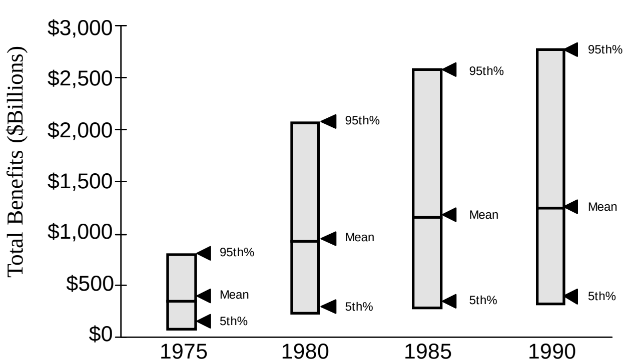
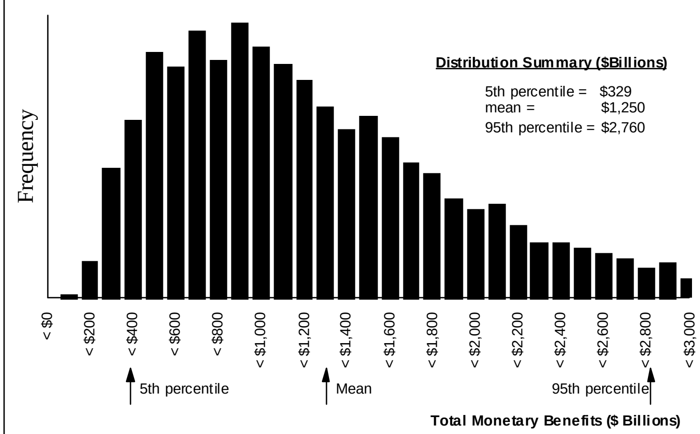


Figure 19. Distribution of 1990 Monetized Benefits of CAA (in billions of 1990 dollars).



On initial inspection, the estimated $1.25 trillion value for monetized benefits in 1990 may seem implausibly large, even though 1990 is the year in which the differences between outcomes under the control and no-control scenarios are at their most extreme. The plausibility of this estimate may seem particularly questionable to some if one considers that the $1.25 trillion value for 1990 is over five percent of the estimated $22.8 trillion value for total 1990 assets of households and nonprofit organizations. Considered from this perspective, $1.25 trillion may seem to represent a large share of total wealth, and some might question whether Americans would really be willing to pay this much money for the reductions in risk achieved by the Clean Air Act and related programs, even if the risk in question involves premature death. However, in the end it is clear that such comparisons are overly simplistic and uninformative because they ignore the magnitude and nature of the welfare change being measured.

First, with respect to the magnitude of the difference in estimated social welfare under the two scenarios, it is important to recognize how severe air quality conditions and health risks would be under the hypothetical no-control scenario. Focusing on ambient particulate matter, the pollutant responsible for the vast majority of the estimated monetary benefits, a comparison of the estimated annual mean concentrations of total suspended particulates (TSP) projected in the U.S. under the no-control scenario with esti-

[64] Comparing Tables 16 and 17, it can be seen that the sum of benefits across endpoints at a given percentile level does not result in the total monetized benefits estimate at the same percentile level in Table 17. For example, if the fifth percentile benefits of the endpoints shown in Table 16 were added, the resulting total would be substantially less than $5.6 trillion, the fifth percentile value of the distribution of aggregate monetized benefits reported in Table 17. This is because the various health and welfare effects are treated as stochastically independent, so that the probability that the aggregate monetized benefit is less than or equal to the sum of the separate five percentile values is substantially less than five percent.

mated annual mean TSP concentrations in other parts of the world[65] indicates that in 1990—

- 60 metropolitan areas in the U.S. would have had higher TSP concentrations than Moscow, Russia
- 7 metropolitan areas would be worse than Bangkok, Thailand
- 6 metropolitan areas would be worse than Bombay, India
- 2 metropolitan areas would be worse than Manila, Philippines
- One metropolitan area would be worse than Delhi, India (one of the most polluted cities in the world)

Under the control scenario, TSP levels in only 3 metropolitan areas were projected to exceed those in Moscow, and none exceeded levels found in the other foreign cities listed above. The principal reason air quality conditions are so poor under the no-control scenario is that air pollution control requirements remain fixed at their 1970 levels of scope and stringency while total economic activity, including polluting activity, grows by 70 percent and population grows by 22.3 percent between 1970 and 1990. Under the severe air quality conditions projected throughout the U.S. in 1990 under the no-control case, an additional 205,000 people would be projected to die prematurely due to the effects of particulate matter, lead, and other criteria pollutants. This represents a very large increase in the risk of premature mortality. Since the estimate that the average loss of life for those who actually succumb to PM exposure related health effects is approximately 14 years, and life-shortening due to lead exposure is even greater, it is no longer surprising that the estimated value of avoiding these severe conditions is so high.

Second, with respect to the nature of the welfare change reflected in the monetized benefit estimate, the concern about the effects of limited budgets constraining Americans' collective ability to pay to avoid these severe no-control scenario conditions is misplaced. In reality, what society actually had to pay to avoid these conditions is measured on the cost side of the analysis, which sums up the total expenditures made by manufacturers and others to achieve these air pollution reductions. The most reasonable estimate of the value Americans place on avoiding those severe no-control scenario conditions, however, is provided by measuring the amount of compensation Americans would have demanded from polluting companies and others to accept, willingly, all of that extra pollution and its associated risks of premature death. Under this concept of welfare change measurement, there is no inherent limit on the amount of money citizens would demand from companies to accept their pollution and so individual personal wealth does not constrain this value.

The monetized benefit estimate presented in this study, therefore, does not necessarily represent an attempt to mirror what Americans would pay out of their own pockets to reduce air pollution from levels they never experienced; rather, it provides an estimate of the value Americans place on the protection they received against the dire air pollution conditions which might have prevailed in the absence of the 1970 and 1977 Clean Air Acts and related programs. Viewed from this perspective, the estimated monetized benefits presented herein appear entirely plausible.

Comparison of Monetized Benefits and Costs

Table 18 presents summary quantitative results for the retrospective assessment. Annual results are presented for four individual years, with all dollar figures expressed as inflation-adjusted 1990 dollars. The final column sums the stream of costs and benefits from 1970 to 1990, discounted (i.e., compounded) to 1990 at five percent. "Monetized benefits" indicate both the mean of the Monte Carlo analysis and the credible range. "Net Benefits" are mean monetized benefits less annualized costs for each year. The table also notes the benefit/cost ratios implied by the benefit ranges. The distribution of benefits changes little (except in scale) from year to year: The mean estimate is somewhat greater than twice the fifth percentile estimate, and the ninety-fifth percentile estimate is somewhat less than twice the mean estimate. The distribution shape changes little across years because the sources of uncertainty (i.e., CR functions and economic valuations) and their characterizations are unchanged from year to year. Some variability is induced by changes in relative pollutant concentrations over time, which then change the relative impact of individual CR functions.

Several measures of "cost" are available for use in this analysis (see Chapter 2). The Project Team

[65] "Urban Air Pollution in Megacities of the World," UNEP/WHO, 1992a, Published by the World Health Organization and United Nations Environment Program, Blackwell Publishers, Oxford, England, 1992. "City Air Quality Trends," UNEP/WHO, 1992b, Published by the United Nations Environment Program, Nairobi, Kenya, 1992.

Table 18. Quantified Uncertainty Ranges for Monetized Annual Benefits and Benefit/Cost Ratios, 1970-1990 (in billions of 1990-value dollars).

	1975	1980	1985	1990	PV
Monetized Benefits					
5th percentile	87	235	293	329	5,600
Mean estimate	355	930	1,155	1,248	22,200
95th percentile	799	2,063	2,569	2,762	49,400
Annualized Costs (5%)	14	21	25	26	523
Net Benefits					
Mean benefits - Costs	341	909	1,130	1,220	21,700
Benefit/Cost ratio					
5th percentile	6/1	11/1	12/1	13/1	11/1
Mean estimate	25/1	44/1	46/1	48/1	42/1
95th percentile	57/1	98/1	103/1	106/1	94/1

Notes: PV=1990 present value reflecting compounding of costs and benefits from 1971 to 1990 at 5 percent.

employs "annualized cost" as the primary cost measure because it measures cost in a fashion most analogous to the benefits estimation method. An alternative measure, "compliance expenditure," is a reasonable cost measure. Some capital expenditures, however, generate a benefit stream beyond the period of the analysis (i.e., beyond 1990). Those post-1990 benefits are not, in general, included in the benefit estimates presented above. The annualization procedure reduces the bias introduced by the use of capital expenditures by spreading the cost of the capital investment over its expected life, then counting as a "cost" only those costs incurred in the 1970 to 1990 period.

The macroeconomic analysis employed for this analysis (see Chapter 2) indicates that compliance expenditures induce significant second-order effects, and it can be argued that those effects should be included in a comprehensive cost analysis. Benefits resulting from compliance expenditures should also induce second-order macroeconomic effects (which would, one would expect, partly or completely offset the estimated second-order adverse effects induced by compliance expenditures). Due to the sequencing of the analytical steps in this assessment, it was not practical to estimate the second-order cost and benefit impacts induced by the estimated health and welfare benefits. Because second-order impacts of benefits are not estimated, the Project Team refrained from choosing as the primary cost measure one that included second-order impacts, and instead employed "annualized costs" as the primary cost measure.

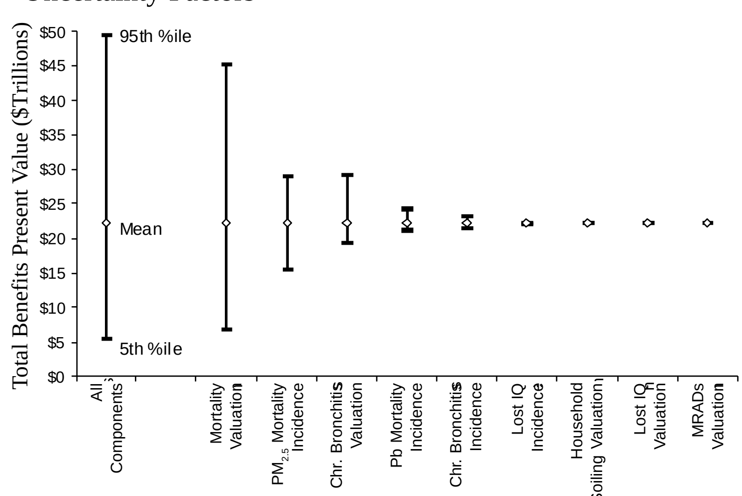
Major Sources of Uncertainty

The methods used to aggregate monetized benefits and characterize the uncertainty surrounding estimates of these benefits have been discussed above, and the resulting estimates of aggregate benefits have been compared to the corresponding estimates of cost. Additional insights into key assumptions and findings can, however, be obtained by further analysis of potentially important variables.

For some factors in the present analysis, both the degree of uncertainty and the direction of any associated bias are unknown; for some other factors, no employable quantitative estimates could be used even though available evidence suggests a positive and potentially substantial value. An example of the latter deficiency is the lack of quantitative estimates for some human health effects, some human welfare effects, and all ecological effects. Despite the exclusion of potentially important variables, it is worthwhile to evaluate the relative contribution of included variables to quantifiable uncertainty in the net benefit estimate. One of these variables, premature mortality valuation, is also given special attention in the subsequent section on alternative results.

The estimated uncertainty ranges for each endpoint category summarized in Table 16 reflect the measured uncertainty associated with both avoided incidence and economic valuation. The Project Team conducted a sensitivity analysis to determine the variables with the greatest contribution to the quantified uncertainty range. The results of this sensitivity analysis are illustrated in Figure 20.

Figure 20. Uncertainty Ranges Deriving From Individual Uncertainty Factors



In this sensitivity analysis, all the inputs to the Monte Carlo uncertainty analysis are held constant (at their mean values), allowing only one variable -- for example, the economic valuation of mortality -- to vary across the range of that variable's uncertainty. The sensitivity analysis then isolates how this single source of uncertainty contributes to the total measured uncertainty in estimated aggregate benefits. The first uncertainty bar represents the credible range associated with the total monetized benefits of the Clean Air Act, as reported above. This captures the multiple uncertainties in the quantified benefits estimation. The rest of the uncertainty bars represent the quantified uncertainty ranges generated by single variables. As shown in Figure 20, the most important contributors to aggregate quantified uncertainty are mortality valuation and incidence, followed by chronic bronchitis valuation and incidence.

Alternative Results

The primary results of this analysis, including aggregate cost and benefit estimates and the uncertainty associated with them, are presented and discussed above. However, although the range of net benefit estimates presented reflects uncertainty in many important elements of the analysis, there are two key variables which require further discussion and analysis: PM-related mortality valuation and the discount rate. This additional treatment is necessary because reasonable people may disagree with the Project Team's methodological choices for these two variables, and these choices might be considered ex ante to significantly influence the results of the study. The purpose of this section, therefore, is to present alternative quantitative results which reflect, separately, (1) an alternative approach to valuation of premature mortality associated with particulate matter exposure, and (2) alternative values for the discount rate used to adjust the monetary values of effects occurring in various years to a particular reference year (i.e., 1990).

PM Mortality Valuation Based on Life-Years Lost

The primary analytical results presented earlier in this chapter assign the same economic value to incidences of premature mortality regardless of the age and health status of those affected. Although this has been the traditional practice for benefit-cost studies conducted within the Agency, this may not be the most appropriate method for valuation of premature mortality caused by PM exposure. Some short-term PM exposure studies suggest that a significantly disproportionate share of PM-related premature mortality occurs among persons 65 years of age or older. Combining standard life expectancy tables with the limited available data on age-specific incidence allows crude approximations of the number of life-years lost by those who die prematurely as a result of exposure to PM or, alternatively, the changes in age-specific life expectancy of those who are exposed to PM.

The ability to estimate, however crudely, changes in age-specific life expectancy raises the issue of whether available measures of the economic value of mortality risk reduction can, and should, be adapted to measure the value of specific numbers of life-years saved.[66] Although the Agency has on occasion performed sensitivity calculations which adjust mortality values for those over age 65, the Agency is skeptical that the current state of knowledge and available analytical tools support using a life-years lost approach or any other approach which assigns different risk reduction values to people of different ages or circumstances. This skepticism is mirrored in the OMB guidance on implementing Executive Order 12866 pertaining to economic analysis methods, which states on page 31:

> *While there are theoretical advantages to using a value of statistical life-year-extended approach, current research does not provide a definitive way of developing estimates of VSLY that are sensitive to such factors as current age, latency of effect, life years remaining, and social valuation of different risk reductions. In lieu of such information, there are several options for deriving the value of a life-year saved from an estimate of the value of life, but each of these methods has drawbacks. One approach is to use results from the wage compensation literature (which focuses on the effect of age on WTP to avoid risk of occupational fatality). However, these results may not be appropriate for other types of risks. Another approach is to annualize the VSL using an appropriate rate of discount and the average life years remaining. This approach does not provide an independent estimate of VSLY; it simply rescales the VSL estimate. Agencies should consider providing estimates of both VSL and VSLY, while recognizing the developing state of knowledge in this area.*

While the Agency continues to prefer an approach which makes no valuation distinctions based on age or other characteristics of the affected population, alternative results based on a VSLY approach are pre-

[66] This issue was extensively discussed during the Science Advisory Board Council review of drafts of the present study. The Council suggested it would be reasonable and appropriate to show PM mortality benefit estimates based on value of statistical life-years (VSLY) saved as well as the value of statistical life (VSL) approach traditionally applied by the Agency to all incidences of premature mortality.

sented below. The method used to develop VSLY estimates is described briefly in Chapter 6 and in more detail in Appendix I.

Table 19 summarizes and compares the results of the VSL and VSLY approaches. Estimated 1970 to 1990 benefits from PM-related mortality alone and total assessment benefits are reported, along with total compliance costs for the same period, in 1990 dollars discounted to 1990 at five percent. The results indicate that the choice of valuation methodology significantly affects the estimated monetized value of historical reductions in air pollution-related premature mortality. However, the downward adjustment which would result from applying a VSLY approach in lieu of a VSL approach does not change the basic outcome of this study, viz. the estimated monetized benefits of the historical CAA substantially exceed the historical costs of compliance.

Table 19. Alternative Mortality Benefits Mean Estimates for 1970 to 1990 (in trillions of 1990 dollars, discounted at 5 percent) Compared to Total 1970 to 1990 Compliance Costs.

Benefit Estimation Method	Benefits PM	Benefits Tot.
Statistical life method ($4.8M/case)	16.6	18.0
Life-years lost method ($293,000/year)	9.1	10.1
Total compliance cost	---	0.5

Alternative Discount Rates

In some instances, the choice of discount rate can have an important effect on the results of a benefit-cost analysis; particularly for those analyses with relatively long time horizons for costs and/or benefits. In this assessment, the discount rate affects only four factors: IQ-related benefits estimates (especially estimates of changes in discounted lifetime income), lifetime income losses due to other health effects (e.g., stroke), annualized costs (i.e., amortized capital expenditures), and compounding of all costs and benefits to 1990. Table 20 summarizes the effect of alternative discount rates on the "best estimate" results of this analysis. Because monetized benefits exceed costs for all years in the analysis period, net benefits increase as the discount rate increases. Because the annual benefit/cost ratio increases as one moves from 1970 toward 1990 (see Table 18 above), benefit cost ratios decline as the discount rate increases (because earlier periods are given greater weight). Overall, the results of the benefit-cost assessment appear to be generally insensitive to the choice of discount rate.

Table 20. Effect of Alternative Discount Rates on Present Value of Total Monetized Benefits/Costs for 1970 to 1990 (in trillions of 1990 dollars).

	Discount rate 3%	Discount rate 5%	Discount rate 7%
Mean Estimated Benefits	19.2	22.2	25.8
Annualized Costs	0.4	0.5	0.7
Net Benefits	18.8	21.7	25.1
Benefit/Cost ratio	48/1	42/1	37/1